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Generalizing Near Set Theory: A Comprehensive Study

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Abstract

Our objective is to tackle the issue of estimating spaces in computational systems by employing generalized topological structure categories. Particle generalization relations form the subbase of some topological spaces. The lower and upper limits of a function can be approximated using these components. Filling out the method of granular computing, whereby a topological structure is obtained and a wide range of topological facts and methods can be applied to the problem at hand.

Introduction

Rough set theory, as proposed by Pawlak (1991, 1982),viewed as a new approach to mathematics for resolving the problem of uncertainty. Difficulties in The fundamental tenet of set theory is that each and Information permeates everything with numbers. Results from the studies conducted by Abu-Donia et al (2007). So, as an example: Red flags that indicate an individual may be sick, recording of a patient's sickness details in a medical chart. Objects Since identical datasets produce identical (sim-large) That's what we know them to be at this point in time. Disregard for accreditation stream that makes use of carefully planned statistics. Theoretical structure for set-based estimation. For the purposes of this definition of "indiscernible, "Gottfried Wilhelm Leibniz's idea that external causes can cancel internal ones. For a secret to persist, all of its obvious uses must have been exhausted. Essentially identical (according to Leibniz's Law of Indiscernibility: From whence originate these mysterious strangers? (Aries et al., 1989). However, Indiscernibility is quantified in Random Set Theory as a percentage of possible examples. based on a set of established standards for conducting operations (attributes). Looked at in aggregate, these indies-A "fundamental configuration" is something that almost everyone is familiar with. A familiarity with the night sky and the planets. Any When molecules of various kinds interact, they tend to enhance one another (precise) set. Unprocessed materials are known as "raw" (imprecise, vague). This means that irregularities will always be present in any set of data. That which cannot be classified in any of these ways members of or opponents to a particular organization. Obviously, it has novel material. Consist of absolutely no boundary parts. For this reason, Incorrectly categorizing borderline situations using previous knowledge in new situations. Therefore, if we adopt this viewpoint, we can only From what we have gathered, we have a hunch that The knowledge infrastructure is all-inclusive. As a result of the care with which There are still some hidden but crucial details in the data. Plus, they seem to be the same item, which is a bonus (or similar). Because of this, the outcome can't be guaranteed. Ideas, in contrast to material objects, can't be neatly categorized. Awareness of how they are constructed if you will. Which methods of investigation you employ will influence the outcomes. Pictures that are only tangentially based on reality (Peters, 2007) in close proximity to one another physically. The near set technique relies on this cutting-edge idea (Peters, 2007; Peters et al., 2007). according to the most basic description (MDL)Invented by Jorma Rissanen in 1983. For MDL to work, identification is essential. speculation on possible interpretations of the data and the corresponding odds. However, NDP is concerned with the domain of an entity, which is denoted by the set X. a label used to identify products that share common qualities. Something like that suggests that there are entities whose presence can be demonstrated with high degree of certainty. that requires the full context to make sense of it. The near set technique can be used to classify people into subsets. representations of data-heavy objects, with an emphasis on feature-filtering technique. Techniques for Isolating Crucial Elements The method considers a wide variety of n sensing combinations. It's time to start looking for the guidelines for taking the test. groupings of things depending on their shared characteristics maximize the information quantity that can be obtained. We assume throughout this article that any notion that exists only in theory is re- There are two distinct concepts that describe a summary of the most persuasive interpretations of the concept. Everything that can be demonstrated by working together is analysed. The concept and the best-case situation are complete in themselves and explain everything. which have parts that can be separated out and examined separately

The maximum and minimum figures are estimates.

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a Gray area where one can sense the presence of truth two of the most common techniques for cleaning up unprocessed data. an invitation to offer feedback on how we interpreted the poll results. There are no underlying statistical presumptions in the proposed approach. finding the best feature value based on a collection of data vectors

in the same niche, and the proposed method of assessment data access measurement in groups similarities and connections to the underlying structure. The close-in approach is dependent on a predetermined list of concerns Among the many important findings from this investigation is We demonstrate how the close set approach can be developed further to achieve broader goals.

Extracting and identifying specifics.

Preliminaries

In rough set theory, ambiguity is communicated not through set membership but through the use of the set's border. For a set to be considered "crisp," it must have a clear border area. If not, the collection is difficult (inexact). When we have insufficient information to provide an exact definition of a set, we find that it has a nonempty border region. Let's pretend we have access to the indiscernibility relation E # U which represents our ignorance of the components of the world (U). We want to describe the set X with regard to the equivalence relation E, and for the sake of simplicity we will suppose that E is an equivalence relation and that X is a subset of U. We'll be using the following general set theory basics to get the job done (Pawlak, 1982).

The equivalence class of E determined by element x is: $[x]_E = \{x' \in X : E(x) = E(x')\}$. Hence E-lower, upper approximations and boundary region of X are:

$$\underline{E}(X) = \bigcup\{[x]_E : X \subseteq U, [x]_E \subseteq X\};$$
$$\overline{E}(X) = \bigcup\{[x]_E : X \subseteq U, [x]_E \cap X \neq \phi\};$$
$$BND_E(X) = \overline{E}(X) - \underline{E}(X).$$

It is easily seen that approximations are in fact interior and closure operations in a topology generated by the indiscernibility relation (Abd El-Monsef et al., 2010). The rough membership function is a degree that x belongs to X in view of information about expressed by E. It defined as

(Pawlak and Skowron, 1994):

$$\mu_X^E(x) : U \to [0,1], \quad \mu_X^E(x) = \frac{|X \cap [x]_E|}{|[x]_E|},$$

where jdenotes the cardinality of A rough set can also be characterized numerically by the accuracy measure of an approximation (Pawlak, 1991) which

is defined as:

$$\alpha_E(X) = \frac{|\underline{E}(X)|}{|\overline{E}(X)|}.$$

Obviously, 0 6 are ox 6 1. If are ðXÞ¼1, X is crisp with re- sect to E (X is precise with respect to E), and otherwise, if are ox < 1, X is rough with respect to E (X is vague with re-sect to E).Underlying the study of near set theory is an interest in classifying sample objects by means of probe functions associated with object features. More recently, the term feature is defined as the form, fashion or shape (of an object).Let F denotes a set of features for objects in a set X. For any feature a 2 F, we associate a function fa that maps X to some

set VA (range of fa).The value of fa ox is a measurement associated with feature a of an object x 2 X. The function fa is called a probe function.

(Pavel, 1993).The following concepts introduced by Peters (2007) and Pe- tars et al. (2006).GAS ¼ðU; F; Nr ; mob Þ is a generalized approximation space, where U is a universe of objects, F is a set of functions representing object features, Nr is a neighbourhood family function

defined as

$$N_r(F) = \bigcup_{A \subseteq P_r(F)} [x]_A, \text{ where } P_r(F) = \{A \subseteq F : |A| = r, 1 \leqslant r \leqslant |F|\}.$$

And ν_{B_r} is an overlap function defined by

$$\nu_{B_r} : P(U) \times P(U) \to [0,1], \quad \nu_{B_r}(Y, N_r(B)_* X) = \frac{|Y \cap N_r(B)_* X|}{|N_r(B)_* X|},$$

where Nr byX – /; Y is a member of the family of neighbour-hoods Nr band mgr. eye; Nr byXin equal to 1, if Nr byX ¼ /.The overlap function mgr. maps a pair of sets to a number in ½0; 1———————— representing the degree of overlap between the sets of ob.-jects with features Br Nr by-lower, upper approximations and boundary region of a set X with respect to r features from the probe functions

B are defined as:

$$N_r(B)_* X = \bigcup_{x:[x]_{B_r} \subseteq X} [x]_{B_r};$$
$$N_r(B)^* X = \bigcup_{x:[x]_{B_r} \cap X \neq \phi} [x]_{B_r};$$
$$BND_{N_r(B)} X = N_r(B)^* X - N_r(B)_* X.$$

Peters introduces the following concepts:

Objects x and x' are minimally near each other if $\exists f \in B$ such that $f(x') = f(x)$. A set X is near to X' if $\exists x \in X, x' \in X'$ such that x and x' are near objects. A set X is termed a near

Generalized near set theory.

In the following, we use a general relation to deduce a new ap-preach to near set theory, consequently we obtain a new gen-earl near lower (upper) approximation for any near set. Also, we introduce a modification of some concepts.

Definition 3.1. Let $f \in B$ be a general relation on a nonempty set X. A special neighborhood of an element $x \in X$ is

$$(x)_{f_r} = \{y \in X : |f(y) - f(x)| \leqslant r\},$$

where $|\ * \ |$ is the absolute value of $*$ and r is the length of neighborhood with respect to the feature f.

Remark 3.1. We will replace the equivalence class in the classical approximations defined by Peters by the special neighborhood defined in Definition 3.1.

Definition 3.2. Let $B \subseteq F$ be a set of functions representing features of $x, x' \in X$. Objects x and x' are minimally near each other if $\exists f \in B$ such that $|f(x) - f(x')| \leqslant r$, where r is the length of a special neighborhood defined in Definition 3.1, with respect to the feature f. Denoted by $xN_f x'$.

Theorem 3.1. *Let $x, y \in X$ and $f \in B$. Then x is near to y if $x \in (y)_{f_r}$ or $y \in (x)_{f_r}$.*

Proof. From Definitions 3.1 and 3.2, we get the proof. □

Theorem 3.2. *Any subset of X is near to X.*

Proof. The proof is obvious. □

Postulation 3.1. Every set X is called near set, near to itself, as every element $x \in X$ is near to itself.

Definition 3.4. Let (X, τ_{ϕ_i}) be topological spaces, where $\phi_i \in B, 1 \leqslant i \leqslant |B|$. Then the lower and upper approximations for any subset $A \subseteq X$ with respect to the feature ϕ_i are defined as:

$$\underline{N}_{\phi_i}(A) = int_{\phi_i}(A) \text{ and } \overline{N}_{\phi_i}(A) = cl_{\phi_i}(A), \text{ where}$$

$int_{\phi_i}(cl_{\phi_i})$ is the interior (closure) with respect to the topology τ_{ϕ_i}, whose subbase is the family of special neighborhoods defined in Definition 3.1.

Definition 3.5. Let (X, τ_{ϕ_i}) be topological spaces, where $\phi_i \in B, 1 \leqslant i \leqslant |B|$. A new near lower and upper approximations for any subset $A \subseteq X$ with respect to one feature of the probe functions B are defined as

$$\underline{apr}_1(A) = \bigcup_{\phi_i \in B} \underline{N}_{\phi_i}(A) \text{ and } \overline{apr}_1(A) = \bigcap_{\phi_i \in B} \overline{N}_{\phi_i}(A).$$

Consequently

$$b_{apr_1}(A) = \overline{apr}_1(A) - \underline{apr}_1(A).$$

Remark 3.3. The new near lower and upper approximations with respect to two features of the probe functions B will be defined as

$$\underline{apr}_2(A) = \bigcup_{\phi_i, \phi_j \in B} \underline{N}_{\phi_i \phi_j}(A) \text{ and } \overline{apr}_2(A) = \bigcap_{\phi_i, \phi_j \in B} \overline{N}_{\phi_i \phi_j}(A), \text{ where}$$

$$\underline{N}_{\phi_i \phi_j}(A) = int_{\phi_i \phi_j}(A) \text{ and } \overline{N}_{\phi_i \phi_j}(A) = cl_{\phi_i \phi_j}(A).$$

Consequently,

$$\underline{apr}_{|B|}(A) = \bigcup_{\phi_1, \phi_2, \ldots, \phi_{|B|} \in B} \underline{N}_{\phi_i \phi_j \ldots \phi_{|B|}}(A);$$

$$\overline{apr}_{|B|}(A) = \bigcap_{\phi_1, \phi_2, \ldots, \phi_{|B|} \in B} \overline{N}_{\phi_i \phi_j \ldots \phi_{|B|}}(A).$$

Definition 3.6. Let (X, τ_{ϕ_i}) be topological spaces, where $\phi_i \in B, 1 \leqslant i \leqslant |B|$. The accuracy measure of any subset $A \subseteq X$ with respect to i features is defined as:

$$\alpha'_i(A) = \frac{|\underline{apr}_i(A)|}{|\overline{apr}_i(A)|}, \quad A \neq \phi.$$

Remark 3.4. $0 \leqslant \alpha'_i(A) \leqslant 1$, $\alpha'_i(A)$ means the degree of exactness of any subset $A \subseteq X$. If $\alpha'_i(A) = 1$, then A is exact set with respect to i features.

Theorem 3.3. *For any subset $A \subseteq X$, $\underline{apr}_i(A)$ and $b_{apr_i}(A)$ are near to $\overline{apr}_i(A)$.*

Proof. Obvious. □

Remark 3.5. A set A with a boundary $|b_{apr_i}(A)| \geqslant 0$ is a near set.

Theorem 3.4. *Every rough set is a near set but not every near set is a rough set.*

Proof. There are two cases to consider

1. $|b_{apr_i}(A)| > 0$. Given a set $A \subseteq X$ that has been approximated with a nonempty boundary, this means A is a rough set as well as a near set.
2. $|b_{apr_i}(A)| = 0$. Given a set $A \subseteq X$ that has been approximated with an empty boundary, this means A is a near set but not a rough set. □

Definition 3.7. Let (X, τ_{ϕ_i}) be topological spaces, where $\phi_i \in B, 1 \leqslant i \leqslant |B|$. The new generalized lower rough coverage of any subset Y of the family of neighborhoods with respect to the probe functions B is defined as

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Table 1 Values features for the objects.

	s	a	r
x_1	0.51	1.2	0.53
x_2	0.56	3.1	2.35
x_3	0.72	2.8	0.72
x_4	0.77	1.9	0.95

$$v_i'(Y, \underline{apr}_i(D)) = \frac{|Y \cap \underline{apr}_i(D)|}{|\underline{apr}_i(D)|},$$

where D is the decision class, means the acceptable objects (Peters, 2007), $\underline{apr}_i(D) \neq \phi$ and if $\underline{apr}_i(D) = \phi$ then $v_i'(Y, \underline{apr}_i(D)) = 1$.

Remark 3.6. $0 \leqslant v_i' \leqslant 1$. It measures the degree that the subset Y coverers the acceptable objects or sure region ($\underline{apr}_i(D)$).

Now, we give an example to explain these definitions.

Example 3.1. Let s, a, r be three features defined on a non-empty set $X = \{x_1, x_2, x_3, x_4\}$ as in Table 1.

If the length of the neighborhood of the feature s (resp a and r) equals to 0.2 (resp 0.9 and 0.5), then

$N_1(B) = \{\xi(s_{0.2}), \xi(a_{0.9}), \xi(r_{0.5})\}$, where

$\xi(s_{0.2}) = \{\{x_1, x_2\}, \{x_1, x_2, x_3\}, \{x_2, x_3, x_4\}, \{x_3, x_4\}\}$;

$\xi(a_{0.9}) = \{\{x_1, x_4\}, \{x_2, x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_3, x_4\}\}$;

$\xi(r_{0.5}) = \{\{x_1, x_3, x_4\}, \{x_2\}\}$. Hence,

$\tau_{s_{0.2}} = \{\{x_2\}, \{x_3\}, \{x_1, x_2\}, \{x_2, x_3\}, \{x_3, x_4\},$

$\{x_1, x_2, x_3\}, \{x_2, x_3, x_4\}, X, \phi\}$;

$\tau_{a_{0.9}} = \{\{x_3\}, \{x_4\}, \{x_3, x_4\}, \{x_2, x_3\}, \{x_1, x_4\},$

$\{x_2, x_3, x_4\}, \{x_1, x_3, x_4\}, X, \phi\}$;

$\tau_{r_{0.5}} = \{\{x_2\}, \{x_1, x_3, x_4\}, X, \phi\}$. Also, we get :

$N_2(B) = \{\xi(s_{0.2}, a_{0.9}), \xi(s_{0.2}, r_{0.5}), \xi(a_{0.9}, r_{0.5})\}$, where

$\xi(s_{0.2}, a_{0.9}) = \{\{x_1\}, \{x_2, x_3\}, \{x_2, x_3, x_4\}, \{x_3, x_4\}\}$;

$\xi(s_{0.2}, r_{0.5}) = \{\{x_1\}, \{x_2\}, \{x_3, x_4\}\}$;

$\xi(a_{0.9}, r_{0.5}) = \{\{x_1, x_4\}, \{x_2\}, \{x_3, x_4\}, \{x_1, x_3, x_4\}\}$. Hence,

$\tau_{s_{0.2}a_{0.9}} = \{\{x_1\}, \{x_3\}, \{x_2, x_3\}, \{x_3, x_4\}, \{x_1, x_3\},$

$\{x_2, x_3, x_4\}, \{x_1, x_2, x_3\}, \{x_1, x_3, x_4\}, X, \phi\}$;

$\tau_{s_{0.2}r_{0.5}} = \{\{x_1\}, \{x_2\}, \{x_3, x_4\}, \{x_1, x_2\}, \{x_1, x_3, x_4\},$

$\{x_2, x_3, x_4\}, X, \phi\}$;

$\tau_{a_{0.9}r_{0.5}} = \{\{x_2\}, \{x_4\}, \{x_1, x_4\}, \{x_3, x_4\}, \{x_2, x_4\},$

$\{x_1, x_3, x_4\}, \{x_1, x_2, x_4\}, \{x_2, x_3, x_4\}, X, \phi\}$.

Also, we find that

$\tau_{s_{0.2}r_{0.5}} \equiv \tau_{s_{0.2}r_{0.5}a_{0.9}}$.

Consequently the product of these features is the features fs; rug, so the feature fag can be cancelled. Now the following example deduces a comparison between the classical and new general near approaches by using the accuracy measures.

Example 3.2. As in Example 3.1 we get Table 2, where Qi XÞ is a family of subsets of X.

Note that, $\alpha_2' = \alpha_3'$ for any subset of X, as $\tau_{s_{0.2}r_{0.5}} \equiv \tau_{a_{0.9}s_{0.2}r_{0.5}}$.

Table 2 Comparison between classical and our new near approaches.

$Q(X)$	α_1	α_2	α_3	α_1'	α_2'
$\{x_1\}$	0	$\frac{1}{3}$	1	0	1
$\{x_2\}$	$\frac{1}{4}$	$\frac{1}{3}$	1	1	1
$\{x_3\}$	0	0	0	1	1
$\{x_4\}$	0	0	0	1	1
$\{x_1, x_2\}$	$\frac{1}{2}$	$\frac{1}{2}$	1	1	1
$\{x_1, x_3\}$	0	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{1}{2}$	1
$\{x_1, x_4\}$	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{3}$	1	1
$\{x_2, x_3\}$	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{3}$	1	1
$\{x_2, x_4\}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{2}{3}$	1
$\{x_3, x_4\}$	$\frac{1}{2}$	$\frac{1}{2}$	1	1	1
$\{x_1, x_2, x_3\}$	$\frac{3}{4}$	$\frac{3}{4}$	$\frac{1}{2}$	1	1
$\{x_1, x_2, x_4\}$	$\frac{3}{4}$	$\frac{3}{4}$	$\frac{1}{2}$	1	1
$\{x_1, x_3, x_4\}$	$\frac{3}{4}$	$\frac{3}{4}$	1	1	1
$\{x_2, x_3, x_4\}$	$\frac{3}{4}$	$\frac{3}{4}$	1	$\frac{3}{4}$	1

Remark 3.7. From Table 2, we note that the classical approx.- extended estimates of close sets are stronger than the traditional approximations of rough sets, but we discover that many sets will be underestimated when using them in practice. absolutely correct. Our topological method for studying close sets has proven to be the most effective. This means that our estimates can serve as a springboard for real-world uses in a wide range of scientific disciplines.

Conclusion

Ma Ny later works have used J.F. Peter's original research as a springboard to improve his lower and higher approximations of close sets. This has allowed us to enhance the family-focused neighbourhood models in a more general parameter field. These texts will help us in ma Ny ways, especially in choosing choices.

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