

HIGHLIGHTS

- Computation model based on Interactive Granular Computing (IGrC) for Intelligence Systems (IcS) is presented and the IGrC model is further developed. In particular, this concerns the role of control of IcS and dialogues with experts for IcS treated as complex granules (c-granules, for short) in IGrC.
- The rough set approach is generalized to approximation of concepts used by control of IcS and compound granules representing approximate solutions of problems to be solved by IcS.
- The fundamental role of information systems defined by Pawlak and their generalization to dynamic information systems in searching for relevant computational building blocks for cognition, including, *e.g.*, approximation spaces, classifiers or information systems themselves is discussed.
- The role of dialogues of ICs with human experts and several challenges related to them are discussed. In particular, their impact on granular computations generated by control of IcS is emphasized.

Proposed reviewers:

A Rough Set Perspective on Intelligence Systems

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Abstract

We discuss the role of rough sets and the basic concept of the rough set approach namely concept approximation in Intelligence Systems (IcS). These IcS deal with complex phenomena. Among them are Business Intelligence Systems, Medical Intelligence Systems, or Risk Management Intelligence Systems. In such systems, data models are induced from data perceived in the continuous interaction of the physical layer of IcS, including human experts, and the computational layer of the IcS.

As the computing model for IcS, we propose the Interactive Granular Computing Model (IGrC). The basic objects of IGrC create complex granules (c-granules, for short) that make it possible to link the abstract and physical worlds. IcS aim to generate computations over c-granules (or networks of them), along which high-quality approximations of the solutions to problems solved by IcS are constructed. We generalize the rough set approach to such cases.

The approximation of objects or concepts is supported by advanced reasoning techniques, much more general than in the Zdzisław Pawlak model of the rough set approach. We discuss the fundamental role of information systems defined by Pawlak and their substantial generalization in searching for the relevant approximation spaces used for approximating concepts or, in a more general setting, c-granules (representing in particular, approximate solutions to problems) related to computations of IcS. Additionally, this work explores the role of information systems, creating a special kind of c-granules, in characterizing computational building blocks for cognition, as defined by Leslie Valiant.

For IcS, dialogues with human experts making decisions are unavoidable. We discuss different aspects of such dialogues and challenges for modeling such dialogues, especially concerning reasoning techniques.

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1. Introduction

Intelligence Systems (IcS) are defined in the literature in different ways. For example, in [1] one can find the following definition:

An intelligence system is an advanced tool that reads, interprets, and interacts with its surroundings. Discover how these systems shape the modern world.

Intelligent Systems (IS) are a type of computer system that can learn and adapt, while AI is a broader concept that encompasses the ability of machines to perform tasks in a human-like way. For IS we do not necessarily assume that these systems are interacting with experts or users. In this paper, we consider Intelligence Systems (IcS) assuming that they are based on a special 'symbiosis' of the decision support systems with experts and/or users aiming to support human experts or users rather than making the right decisions in isolation from them (see Fig. 1). This point of view is characteristic for Human-Centered AI and Human-in-the Loop Machine Learning [2, 3, 4]. In the case of decision support systems (or IS) dealing with complex phenomena, we do not have yet enough powerful reasoning tools to eliminate humans in the decision making process. One of the reason is that still there are some 'white spots' in available reasoning techniques which could support systems to a satisfactory degree to deal with common sense reasoning, in particular with reasoning based on experience, *e.g.*, with reasoning by analogy (see, *e.g.*, [5, 6, 6]).

From the point of view of our considerations IcS can be treated as special cases of IS because they are aiming to deliver, on the basis of collected data and reasoning about perceived data, computational building blocks (special c-granules) for humans that are necessary for comprehension by them the perceived situations satisfactory for making the right decisions. In particular, this shows a strong link of IcS with Explainable AI (XAI) (see, *e.g.*, [7, 8, 9]).

Nowadays, are developed different types of IcS [1] like Business IcS [10], Medical IcS [11, 12, 13] or Risk Management IcS [14, 15]. Each of them have some specificity. For example, Business IcS are offering modern business management expertise and cutting-edge technologies, both under one roof. They provide professional services empowering enterprises to stay focused on their core business goals and objectives during executing and delivering management-oriented technology solutions. Business IcS should provide high quality, sustainable, and tangible Information Technology & Business Solutions as well as Services [16].

There is a need for developing solid foundations for IcS on which the design of the high quality IcS systems can be realized. This paper presents a step toward developing such foundations for IcS.

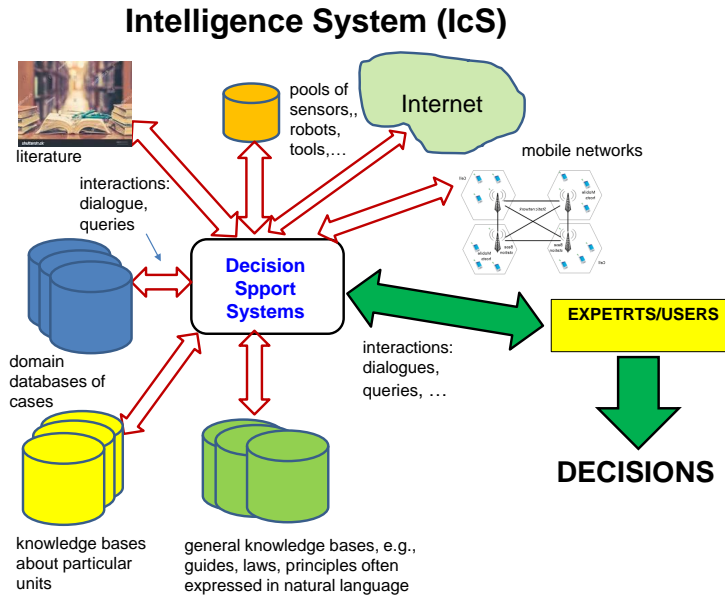


Figure 1: Interactions of IcS with abstract and physical objects, in particular with humans.

In particular, in developing the mentioned above foundations one should take into account several issues related to the following queries:

- How IcS are able to perceive the complex dynamically changing situations in the physical and abstract worlds to a degree making it possible to make the right decisions?
- What is the relevant computing model on which IcS can be grounded, in particular what are the objects used by IcS in their computations?
- What are the necessary reasoning techniques on the basis of which control module of IcS is aiming to generate computations realizing their goals?
- How to characterize the computational building blocks for cognition, *i.e.*, block on which can be grounded understanding the perceived situations to a satisfactory degree for making the right decisions?
- What are the relevant languages and reasoning techniques for performing dialogues between decision support systems and experts and/or users creating parts of IcS?
- What is the role of information systems (defined by Pawlak) in the characterization of the computational building blocks for cognition?

- How the rough set approach should be extended to deal with the issues related to the formulated questions and problems to be solved by IcS, *e.g.*, to deal with the problem of constructing the high quality approximate solutions of problems which IcS are aiming to solve?

Certainly, it is not possible to discuss in detail all of the above issues one paper. In the sequel, we concentrate on necessary generalization of the rough set approach, in particular information (decision) systems defined by Pawlak for dealing with these issues. In particular, we discuss the crucial role of information systems (decision) systems with this respect.

To realize this, first it is necessary to present a relevant computing model on which IcS can be grounded. The reader may recognize that the mentioned above term ‘computational building blocks’ was introduced by Leslie Valiant who considers the problem of characterizing the computational building blocks for cognition as the main problem of AI [17]. In the presented in the paper approach, these ‘computational building blocks’ are modeled by complex granules (c-granules, in short) which are the basic objects in Interactive Granular Computing (IGrC) (see, *e.g.*, [18, 19, 20, 21, 22, 23] and [24, 25]). C-granules are making it possible to deal with abstract as well as with physical objects. Such objects are necessary in developing tools for modeling of perception. This is one of the main difference between IGrC and Granular Computing (GrC). In GrC are investigated information granules embedded in the abstract space (see, *e.g.*, [26, 27, 28, 29, 30]). Moreover, in [31] it is mentioned the lack of theoretical foundations of GrC. In the mentioned above papers on IGrC we are aiming to develop foundations for the IGrC model and this paper is a step for further developing such foundations.

It is important to recognize the necessity of proper modeling of IcS control module. IcS control provides a proper interaction mechanisms for IcS dealing with the environment consisting of abstract and physical objects. It is aiming to generate granular computations along which approximate solutions of problems to be solved by IcS are constructed like classifiers, clustering, compound chemicals or medicine [32]. These approximate solutions are constructed along granular computations using c-granules as computational building blocks for cognition and construction of approximate solutions with the high quality.

IcS are aiming to provide the high quality approximate solutions of the considered problems. Using the relevant specification of a problem P , in the family of approximate solutions of P is distinguished a vague concept ‘approximate solutions with high quality’. IcS is aiming to use the relevant approximation spaces to define the regions of approximation of such concept, *i.e.*, its lower and upper approximation as well as boundary region. Next, in the framework of rough sets one can consider the problem of generation by IcS of approximate solution(s) belonging to such regions, *e.g.*, to the lower approximation.

This paper explores the role of information systems in the process outlined above. We demonstrate how Pawlak’s information systems can be generalized to function effectively as computational building blocks in the processes for understanding situations related to problem specification and finding high-quality

101 approximate solutions. In particular, we discuss how to discover relevant ap-
 102 proximation spaces for approximating the concept of ‘high-quality approximate
 103 solutions’ (the lower approximation of the concept ‘approximate solutions of
 104 a given problem’). Additionally, we outline how the IcS control generates ob-
 105 jects from different approximation regions, *e.g.* objects belonging to the lower
 106 approximation of the considered concept.

107 In generation of granular computations, IcS control should take into account
 108 the necessity of satisfying different criteria, (*e.g.* related to business or risk re-
 109 quirements) as well as the fact that the reasoning tools provided by IcS control
 110 can not be fully automatic but they should be also based on dialogues with ex-
 111 perts and/or users. Moreover, due to the fact that IcS are dealing with complex
 112 phenomena it is not possible to base the approach on classical mathematical
 113 modeling as it was observed by many top researchers (see, *e.g.*, [33]) but is
 114 necessary to provide reasoning tools making it possible continuously search for
 115 proper data in the environment to answer, in particular for queries related to
 116 *what, why, how, when* etc. the new data should be perceived to guarantee the
 117 proper modeling of computational building blocks for cognition and solutions
 118 (granules). One can observe that this is related to attention mechanism, already
 119 discussed by Aristotle [34].

120 In our discussion, we also refer to the recent project Label-in-the-Loop
 121 Project (LITL) [35] or [36] concerning discovery of the high quality learning
 122 classifiers supported by dialogue with experts.

123 This paper is structured as follows. In Section 2 we recall the notion of
 124 information system and the model of rough sets introduced by Pawlak. Next,
 125 in Section 3 we discuss the multi-relational approach to rough sets, in particular,
 126 multi-relational approximation spaces and their relationships with information
 127 systems. We also emphasize that this model can be taken as the basis for many
 128 complex optimization processes related, *e.g.*, to feature selection and extraction
 129 or classifiers generation. In Section 4, we discuss motivation and intuition which
 130 was leading us to IGrC. Sections 5 and 6 include a discussion on generalization of
 131 information systems to dynamic objects under control of IcS as well as their role
 132 in characterization of computational building blocks for cognition by control of
 133 IcS together with motivations for the adaptive rough set approach. Section 7 is
 134 dedicated to dialogues of IcS with human expert supporting characterization of
 135 computational building blocks for cognition. In particular, it is shown that the
 136 architecture of interfaces of IcS with human experts should be equipped with
 137 numerous modules supported by advanced reasoning techniques. Developing
 138 such modules and reasoning techniques requires solving several discussed in this
 139 section challenges. Section 8 presents an outline of the Labeling in the Loop
 140 (LITL) project. The roadmap for dialogues in IcS is discussed in Section 9.
 141 Perspectives of rough sets in IcS are presented in Section 10. Finally, Section 11
 142 concludes the paper.

143 2. Rudiments of information systems

144 Advantages of information systems in specification and modeling of complex
 145 tasks and representation of complex domain knowledge are known for years (for
 146 details see, *e.g.*, [37, 38, 39, 40, 41, 42]). In this section we recall the basic
 147 definition with some additional comments concerning its relationship with the
 148 definition of the Pawlak model of rough sets based on indiscernibility relation
 149 and multi-relational rough sets.

150 Let us recall the basic definitions related to information systems [38].

151 **Definition 1.** *A tuple $IS = (U, A, \{Val_a\}_{a \in A}, f)$ is called an information sys-*
 152 *tem, where*

- 153 • *U is a non-empty set of objects;*
- 154 • *A is a non-empty set of attributes;*
- 155 • *Val_a is a non-empty set of values for each attribute a ;*
- 156 • *$f : U \times A \rightarrow \cup \{Val_a : a \in A\}$ assigns a unique value from Val_a to each*
 157 *$f(x, a)$ for $x \in U$ and $a \in A$.*

158 Equivalent to Definition 1, the notion of information system can also be defined
 159 as follows.

160 **Definition 2.** *A pair $IS^* = (U, A)$ is called an information system [38], where*
 161 *U is a non-empty universe of objects and A is a non-empty set of attributes.*
 162 *Each attribute $a \in A$ is represented as a function $a : U \rightarrow V_a$ where V_a is the*
 163 *set of values of the attribute a , called the domain of a .*

164 Information systems are also defined as pairs (U, A) , where U is a finite set
 165 of objects and A is a set of attributes, *i.e.*, functions from U into the set V_a of
 166 values of a .

167 For any $x \in U$ the signature of x relative to $B \subseteq A$ is defined by $inf_B(x) =$
 168 $\{(a, a(x)) : a \in B\}$ ¹.

169 **Definition 3.** *Given an information system $IS = (U, A, \{Val_a\}_{a \in A}, f)$ and a*
 170 *set $B \subseteq A$, an indiscernibility relation $IND(B)$ on U is defined as follows.*

$$(x, y) \in IND(B), \text{ if and only if } inf_B(x) = inf_B(y).$$

171 For any $B \subseteq A$ we define multi-relational approximation space by

$$AS_B = (U, \{IND(\{a\})\}_{a \in B}).$$

172 Contrary to the Pawlak model of rough sets the concept approximation
 173 over the multi-relational approximation space is not defined uniquely what was

¹We also used notation for signature of a given object x relative to the considered information system, *i.e.*, $inf_{IS}(x)$.

174 observed many years ago (see, *e.g.*, [43, 44]). Hence, in searching for the relevant
 175 concept approximation one should also search for the proper approximation
 176 definition.

177 Information systems with distinguished decisions, called decision systems,
 178 are tuples $DS = (U, C, D)$, where $(U, C \cup D)$ is an information system and
 179 $C \cap D = \emptyset$. The attributes from C and D are called conditional and decision
 180 attributes, respectively.

181 For any decision system $DS = (U, C, D)$ one can consider a generalized
 182 decision function $\partial_{DS} : U \rightarrow P(Inf(D))$ defined by

$$\partial_{DS}(x) = \{i \in Inf(D) : \exists x' \in U [(x', x) \in IND(C) \text{ and } inf_D(x') = i]\}, \quad (1)$$

183 where $P(Inf(D))$ is the powerset of the set $Inf(D)$ of all possible decision
 184 signatures over D , *i.e.*, $Inf(D) = \{inf_D(x) : x \in U\}$.

185 The decision system DS is called consistent (deterministic) if $|\partial_A(x)| = 1$ for
 186 any $x \in U$. Otherwise, DS is said to be inconsistent (non-deterministic). Hence,
 187 a decision system is inconsistent if it consists of some objects with different
 188 decisions but indiscernible with respect to the conditional attributes. Any set
 189 consisting of all objects with the same generalized decision value is called a
 190 generalized decision class.

191 3. Multi-relational approximation spaces

192 In this section, we present examples showing that many problems to be
 193 solved by IcS are optimization problems based on searching for the (semi-) opti-
 194 mal spaces in large families of approximation spaces. Among them are problems
 195 of data reduction, attribute (feature) selection, and feature extraction (feature
 196 engineering) in Machine Learning (ML) [45, 46, 47, 48]. We emphasize the
 197 role of information systems in searching for the relevant approximation spaces
 198 by showing that the searching can be based on the space of the information
 199 (decision) systems representing the approximation spaces.

200 The beginning of multi-granulation rough set approach is usually referred to
 201 papers from 90-ties of the XX century by Cecylia Rauszer and Helena Rasiowa
 202 with Victor Marek (see, *e.g.*, [43, 49, 50, 51]). They considered a team of agents
 203 having at their disposal indiscernibility relations and considered, in particular
 204 for any object aggregation of their voting *for* and *against* of a particular decision.

205 **Definition 4.** *A multi-relational approximation space is any tuple*

$$AS = (U, \{r\}_{r \in R}),$$

206 *where R is a set of binary relations over a set U .*

207 The Pawlak model of rough sets is defined using an approximation space

$$AS = (U, r),$$

208 *where U is a finite set and r is an equivalence relation over U .*

Then, for any $X \subseteq U$ is defined its lower $LOW(r, X)$ and upper approximation $UPP(r, X)$ by $\{x \in U : [x]_r \subseteq X\}$ and $\{x \in U : [x]_r \cap X \neq \emptyset\}$, respectively. Moreover, the boundary region $BN(r, X)$ is defined by $UPP(r, X) \setminus LOW(r, X)$.

From these definitions, one can observe that in the Pawlak model, the approximation space is treated as given a priori, and approximations are defined relative to this approximation space. However, in general, we search for approximations of concepts over an extension of U . This requires developing reasoning techniques to support optimization in searching for the relevant approximation spaces from different, often huge, families of approximation spaces (see, *e.g.*, [45, 46, 48, 32, 32]). We discuss the role of information systems in this searching process.

One can observe that the Pawlak model of rough sets based on information systems is directly related to multi-relational approach too.

Any information system IS defines a multi-relational system

$$AS_{IS} = (U, \{r_a\}_{a \in A}),$$

where $r_a = IND(\{a\})$ for $a \in A$.

Also any multi-relational system $(U, \{r\}_{r \in R})$ defines an information system $IS^* = (U, A^*)$, where $A^* = \{a_r : r \in R\}$, and $a_r(x) = f_r([x]_r)$ for $x \in U$, where f_r is a bijection of the partition U/r of U defined by r onto $\{1, \dots, |U/r|\}$. One can observe that the indiscernibility relation $IND(A^*)$ of IS^* is equal to

$$\bigcap_{r \in R} r.$$

Let us note that the indiscernibility relation $IND(A) = \{(x, y) \in U : a(x) = a(y) \text{ for all } a \in A\}$ of IS is invariant to renaming of attribute values. More formally, $IND(A) = IND(F(A))$, where $F(A) = \{f_a \circ a : a \in A \text{ \& } f_a \text{ is a bijection of } V_a \text{ onto } V_a\}$ and $(f_a \circ a)(x) = f_a(a(x))$ for $x \in U$.

The idea of the multi-relational approach to rough sets was further developed by other researchers (see, *e.g.*, [52, 53, 54, 55, 56, 57, 58]). In particular, the approach has been extended to covering based approach [59, 60], where in multi-relational approximation spaces are considered *e.g.*, tolerance, similarity or even arbitrary binary relations.

In multi-relational approximation spaces, we represent objects based on signatures.

These signatures are used to capture the relationships between objects and a set of attributes. For single attributes, equivalence classes are represented by descriptors. These descriptors take the form (a, v) , where a is the attribute and v is the value of that attribute for a specific object x . The intersection of equivalence classes for single attributes is then described by combining their corresponding descriptors using conjunctions. The situation becomes different when we consider fuzzy sets (or rough fuzzy sets) as semantics for signatures of objects. First, these fuzzy sets are defined over equivalence classes of the original attributes. Then, descriptors representing the fuzzy sets are connected by fuzzy connectives in constructing formulas from signatures. These connectives, being

250 generalization of conjunction, determine how the fuzzy sets corresponding to
 251 aggregations of descriptors are defined. One should also note that the IcS control
 252 may use some strategies for discovery of these connectives from data [61]. In
 253 this way, one can create expressive languages to describe concepts (c-granules)
 254 that serve as building blocks for understanding perceived situations. In the
 255 existing solutions, these languages are proposed by experts in dialogues of IcS
 256 with them.

257 Here, we would like to mention only a relationship of multi-relational ap-
 258 proximation spaces with finite universes U with information systems. For any
 259 such multi-relational system one can construct strongly related to it an
 260 information system. Any of relation r from such spaces can be represented by
 261 a family of neighborhoods $r(x) = \{y \in U : xry\}$, where $x \in U$. One can con-
 262 sider the family of sets generated from such neighborhoods by set theoretical
 263 operations as the family of definable sets. In this way is obtained a Boolean
 264 algebra of sets generated from the neighborhoods. One can also define an in-
 265 formation system with the universe of objects U and binary attributes that
 266 are characteristic functions of these neighborhoods. One can observe that the
 267 family of definable sets of such information system is equal to the family of de-
 268 finable sets of the original multi-relational approximation space. However, one
 269 should be aware that for practical applications the obtained in this way infor-
 270 mation systems can create problems because of the huge number of attributes.
 271 Moreover, for practical applications one should look for constructive methods of
 272 discovery of the relevant definable sets for approximation of considered concepts
 273 what corresponds, *e.g.*, to problems of feature engineering in ML. These defin-
 274 able sets can be treated as examples of computational building blocks necessary
 275 for cognition (using terminology of Valiant [17]) or c-granules in IGrC. One
 276 should note that searching for relevant computational building blocks should
 277 be supported by reasoning taking into account the risk of overfitting and the
 278 description length of the blocks. This is also related to Minimum Description
 279 Length (MDL) principle [62]. This may be illustrated when one extends a given
 280 multi-relational approximation space $AS = (U, \{r\}_{r \in R})$ with a given family R
 281 of equivalence relations by adding to R new equivalence relations r' which are
 282 coarser than some $r \in R$ and next aiming to approximate a given partition of
 283 the universe of objects by a given decision attribute with the high quality using
 284 this new extended multi-relational approximation space and the quality measure
 285 based on MDL. Searching for semi-optimal solutions in this new, usually large
 286 multi-relational approximation space can be successfully supported by Boolean
 287 reasoning (see, *e.g.*, [47, 48]).

288 It is important to note that families of partitions corresponding to rele-
 289 vant equivalence relations for solving a given problem may be defined in many
 290 different ways. For example, in the case of construction of (binary) decision
 291 trees [45] these partitions can be defined by single equivalence classes and their
 292 complements and searching is based on selecting in each step of decision tree
 293 construction of the ‘best’ equivalence class relative to some measures base, *e.g.*
 294 on entropy. It’s important to remember that there are many ways to define
 295 families of partitions based on equivalence relations relevant in searching for so-

lution of a specific problem. For example, in decision tree construction (like the binary trees) [45], these partitions can be defined using single equivalence classes and their complements. At each step of decision tree construction, searching is based on choosing the 'best' (using specific criteria like entropy) equivalence class among such partitions. Another example, can be related to classification by ensembles (see, *e.g.*, [63]). In this case, searching for information systems or family of equivalence relations on the basis of which members of ensembles are constructed plays the important role.

One should note that instead of binary relations over U one can consider fuzzy relations or relations obtained by combination of rough and fuzzy approaches. This approach based on combination of rough and fuzzy approaches defines important spaces of computational building blocks for cognition. In particular, these blocks may be defined by rough-fuzzy aggregation of neighborhoods. This approach was used successfully in many projects (see *e.g.*, [64, 65, 66, 67, 68, 69, 70, 71]).

The discussed above simple multi-relational models $(U, \{r\}_{r \in R})$ generated by information systems were used with a special kind of reasoning, called Boolean reasoning, in searching for solutions of many problems related to reduction of attributes, discretization or symbolic value grouping (see, *e.g.*, [47, 48]). Discretization or symbolic value grouping is related to searching for the optimal transformation of a given multi-granular system AS_{IS} to a multi-granular system $AS_{IS'} = (U, \{r'_a\}_{a \in A'})$, where $A' \subseteq A$ and for any $a \in A'$ r'_a is coarser than r_a , (*i.e.*, $[x]_{r_a} \subseteq [x]_{r'_a}$ for $x \in U$) and

$$IND(A) = IND(A')$$

as well as the sum

$$\sum_{a \in A'} |U/r'_a|$$

is minimal. Usually, this problem is considered for decision systems and then the formulation should be accordingly changed [47, 48]. We would like to emphasize here that quite often we deal with optimization problems related to searching for the optimal approximation space. Hence, reasoning techniques supporting searching for the (semi-)optimal solutions are of great importance.

One should also bear in mind that in the case of multi-relational approximation spaces with relations different from equivalence relations the definition of concept approximation is not unique (see, *e.g.*, [44, 72]) and in applications one should provide reasoning tools supporting searching for the relevant schemes of concept approximation.

Moreover, in the case of multi-relational approximation spaces the sets U as well as the set of relations are not necessarily finite. Such a situation is typical for problems of feature extraction (feature engineering). For example, one can consider as the set of attributes the characteristic functions of half-spaces defined by hyperplanes defined by some real-value attributes (see, *e.g.*, [47, 73].)

It is worthwhile mentioning here the relationships of the covering rough set approach with information systems. First of all, let us observe that in the

definition of information systems by Pawlak together with the value sets V_a is considered the equality $=$, *i.e.*, the relational structure $(V_a, =)$. In discussion on discretization problem, we consider the relational structures (V_a, \leq) , where V_a is a subset of the set of reals and \leq is a linear order. Considering similarity relations over V_a leads to relational structures of the form (V_a, ρ_a) . Together with these relational structures over the value sets of attributes are considered languages of formulas with semantics expressed by subsets of the value sets or their Cartesian products. The characteristic functions of these sets can be considered as possible new attributes. Moreover, they can be used as constraints in aggregation of information systems for filtering tuples of objects satisfying these constraints (see, *e.g.*, [74, 75]). This can also be used in definition of types of information systems discussed in Section 5.

The discussed approach allows us to generalize the indiscernibility relation defined in information systems as an equivalence relation to the indiscernibility being tolerance, similarity relation (see *e.g.*, [76]) or even general binary relation over signatures of objects (see, *e.g.*, [77, 78]). More formally, in generalized information systems IS_{IS_τ} , where τ is a similarity relation over signatures of objects from U , objects $x, y \in U$ are τ -indiscernible in symbols

$$xIND(IS_\tau)y \text{ if and only if } inf_{IS_\tau}(x) \tau inf_{IS_\tau}(y).$$

In one of the above discussed cases we deal with the optimization problem in infinite space. Moreover, one can also consider another important problem for ML related to discovery of languages from which the relevant attributes should be extracted [45, 46].

Let us note that searching for approximation of concepts in the space of all definable sets *i.e.*, arbitrary unions of indiscernibility classes) may be infeasible from the point of view of computational complexity. Hence, these methods are restricted to searching in subspaces of this space, *e.g.*, defined by definable sets determined by intersection of some equivalence classes from R .

4. IGrC - motivation and basic intuition

In this section, we present some an intuitive explanation of some basic concepts related top IGrC.

We have selected the IGrC model as the basis for developing theoretical foundations for the design and analysis of IcS dealing with complex phenomena in the physical world.

In the considered case, according to opinions of many researchers, classical mathematical modeling is not satisfactory (see *e.g.*, [33]). Moreover, in [79] it is noted that there is a necessity to modify the Turing test in order to synchronize four important areas of AI research (language, reasoning, perception, and action), as each has regrettably diverged into a fairly independent area of research. However, one should take into account that when dealing with perception, the computing model should consider not only abstract objects, but also physical objects. The computing model should enable continuous interaction between

379 the system and the physical environment, allowing for the collection of relevant
380 data which can be used to infer data models temporarily characterized by the
381 high quality.

382 The basic objects in IGrC are complex granules (c-granules, for short). They
383 consists two layers: informational and physical. In the informational layer is
384 stored information about perceived situations as well as specifications of tasks
385 realized over them as well as information about the expected results of realiza-
386 tion of these tasks in the physical world. This information is labeling specifica-
387 tions of spatio-temporal windows (addresses) describing regions of the physical
388 space where the information is perceived.

389 The physical layer of c-granule consists parts like `soft_suit`, `link_suit` and
390 `hard_suit`. `Soft_suit` consists of physical objects directly accessible, *i.e.*, objects
391 which properties can be decoded by measurements into the information layer or
392 objects into which some relevant information from the information layer can be
393 encoded. This is realized by special elementary c-granules generated by control
394 of c-granules. Information about physical objects which are not directly accessi-
395 ble is inferred by reasoning tools using knowledge bases or physical laws. Hence,
396 computations in IGrC depend on physical laws contrary to the Turing model
397 [80]. In `link_suit` are physical objects used for transition of interactions from
398 `soft_suit` to `hard_suit` and `hard_suit` contains physical objects to be perceived
399 according to the specifications of spatio-temporal windows represented in the
400 information layer. C-granules are under control of other c-granules or their own
401 control.

402 For simplicity of reasoning, we consider here the case when c-granules are
403 under the control of of IcS which can be treated as a higher order c-granules.
404 This control is responsible for generating computations of IcS. The computa-
405 tions are sequences of c-granules (or their networks including information about
406 relationships of other c-granules which are parts of the networks). IcS is aim-
407 ing to generate such computations realizing in the best way the task of IcS,
408 *i.e.*, they are aiming to generate computations along which the high quality of
409 approximate solutions of problems to be solved by IcS are constructed. These
410 approximate solutions of problems may concern classifiers or compound physical
411 objects like sensors, robots or chemical components.

412 In each step of computation, the control module (CM) of IcS verifies whether
413 the information about the current situation is satisfactory to initiate the ap-
414 propriate transformation of the current c-granule configuration (network of c-
415 granules). This may involve suspending, modifying existing c-granules, or gen-
416 erating new ones. CM includes a special implementation module (IM) respon-
417 sible for realization the transformation specifications in the physical world. In
418 essence, the IM realizes the so-called physical semantics of the transformations'
419 specifications. Here's an idea how it works: The specifications of these transfor-
420 mations are included on the right-hand side of rules located in the rule module
421 (RM) of CM. In each step, the RM checks if the information about the cur-
422 rently perceived situation matches the left-hand side of any rules. If there's a
423 match, the RM uses reasoning mechanisms to resolve any conflicts among these
424 rules. If the conflicts can be resolved, the rule module selects the rule for exe-

425 cution. Otherwise, it suggests gathering more information about the perceived
 426 situation. The execution of the rule involves realizing the transformation spec-
 427 ification from its left-hand side. The IM is responsible for carrying out this
 428 transformation in the physical world. The set of rules in the RM can be viewed
 429 as a complex game involving intricate rules composed out of vague concepts
 430 (learned by the IcS control) labeled by transformations. The RM is adopted
 431 according to perceived changes by CM. For more details about CM, the reader
 432 is referred to [23].

433 The control consists several other important modules. More detailed de-
 434 scription of control is included in the cited paper on IGrC (see, *e.g.*, [18, 19,
 435 20, 21, 22, 23, 24, 25, 32]). The RM plays one of the most important role of
 436 the control of IcS. In the simplest case, the rules are embedded in this mod-
 437 ule by designers. However, in many cases these rules should be learned and
 438 changed according to perceived changes. The central role in the control of IcS
 439 play reasoning techniques supporting the IcS control in its behavior.

440 IGrC goes beyond abstract concepts like information granules in GrC. It
 441 also handles granules that interact with the physical world. The control of IcS
 442 is equipped with IM responsible for realization so called physical semantics. The
 443 IM takes specifications of associations (a broader term than mathematical func-
 444 tions) and generates or uses existing configurations of physical objects. It then
 445 initializes interactions within these configurations and allows the IcS control to
 446 perceive properties related to the object interactions. Based on this perceived
 447 information, along with knowledge bases and physical laws, the IcS control can
 448 infer properties of the perceived objects as results of the realized association.
 449 It's important to note that these inferred properties might differ from expecta-
 450 tions due to environmental interactions (see Fig. 2). If the differences between
 451 the expected and perceived results of realization of transformations are too large
 452 than CM is looking for adaptation of rules.

453 **5. Information systems and their role in characterization of compu-** 454 **tational building blocks for cognition by the control of IcS**

455 Leslie Valiant formulated the main problem of Artificial Intelligence (AI) as
 456 follows [17]:

457 *A fundamental question for artificial intelligence is to character-*
 458 *ize the computational building blocks that are necessary for cognition.*

459 We propose to model these computational building blocks using complex
 460 granules (c-granules), which are the fundamental objects of IGrC. These gran-
 461 ules allow us to link two worlds, namely the abstract and the physical, which
 462 is necessary for dealing with perception [81, 82]. Granular networks, which are
 463 a higher order c-granules obtained from c-granules by linking them by some
 464 relations, and computations over them in IGrC are used by IcS to comprehend
 465 the perceived situation to a satisfactory degree for making the right decisions.

466 In the context of Granular Computing (GrC), information granules can be
 467 seen as a specific type of c-granule. This allows us to focus on the specifications

ASSOCIATIONS AND THEIR PHYSICAL SEMANTICS

$f: X \rightsquigarrow_g Y$ where g is a given c -granule

- X – defined in set theory, elements of X are stored (represented) in informational layer of c -granule g (e.g. control of IcS),
- Y – physical space, not definable in set theory,
- f – association between X and Y realized by c -granule g using

physical semantics:

- **implementation:** for a given $x \in X$ and a specification of f control of g is constructing a physical structural object o_x (with dynamics controlled by g relative to its local time) providing a 'physical pointer' from a part of o_x in which x has been encoded to the associated (by f) to x a physical object in o_x (pointed out by a spatio-temporal window specification represented in the physical layer of g),
- **perception:** some properties of parts of o_x and properties of interactions between them (and with the environment) are perceived by control of g (in particular by decoding from some parts of o_x into informational layer of g) and used in **reasoning by g** toward providing representation of information about the object associated to x by f .

Figure 2: Associations and their physical semantics.

of c -granules, which are represented by information granules. This is because we assume that these specifications are correctly implemented in the physical world and remain unchanged by environmental external to them interactions. Therefore, the computational building blocks needed for cognition include both information granules and c -granules. C -granules are generated by control of IcS using reasoning techniques. This control aims to construct high-quality approximate solutions for problems that IcS needs to solve. These computational building blocks can take various forms, including patterns, clusters, information systems, classifiers, and physical objects such as new sensors, robots, or chemical compounds.

In IGrC we follow the main idea of perception presented in [81]:

The main idea of this book is that perceiving is a way of acting. It is something we do. Think of a blind person tap-tapping his or her way around a cluttered space, perceiving that space by touch, not all at once, but through time, by skillful probing and movement. This is or ought to be, our paradigm of what perceiving is.

Information systems are the basic objects in modeling perception based on this idea. However, several modification of the definition presented above are necessary, in particular:

- information systems should be open to interaction with the control of IcS and the physical world;

- 489 • control of IcS should provide skills for
 - 490 1. discovery of the right types of objects represented in particular in-
491 formation systems;
 - 492 2. implementation in the physical world specifications of perception
493 tasks represented in objects of information systems;
 - 494 3. discovery of the relevant properties of the results of sensory measure-
495 ments and actions over perceived configurations of physical objects.

496 Let us now add some comments on management in IcS.

497 The c-granules (with control) hold specific pieces of information stored in
498 their informational layers. Among these pieces are information systems. An
499 IcS typically manages multiple information systems. Therefore, IcS control
500 requires a proper addressing mechanism (realized by spatio-temporal windows
501 or addresses) to locate the relevant information system, considering both space
502 and time.

503 Each information system, identified by its address, stores objects of a prede-
504 fined type. The type of these objects is defined by a formula that allows the IcS
505 control to determine if a piece of information sent by the IcS control can modify
506 the system and how. For instance, the type might specify that the system holds
507 objects defined by a spatio-temporal window describing where specific attributes
508 should be measured. It could also include time information, such as the start
509 time for the measurement and the expected duration.

510 Information systems can store more complex object types. These could in-
511 clude, *e.g.*, properties of segments from different multi-time series that the IcS
512 control perceives during measurements. These segments could be aggregated
513 into clusters or even more intricate structures. Additionally, types can hold
514 properties related to interactions with physical and abstract objects. These
515 properties might also include conditions expressing relationships between at-
516 tributes, such as specifying that certain parts of the observed objects are phys-
517 ically close.

518 Formally, these types can be represented as formulas $\alpha(x)$ in a specific lan-
519 guage. When checking if information *inf* is relevant for a particular information
520 system *IS*, the variable x in the formula is replaced with the information *inf*.
521 This information describes how the IcS control intends to modify *IS* by adding
522 a new object to its collection.

523 Let us consider an illustrative example in which this new object *o* is defined
524 by information *inf* in the format:

$$w : a_1, \dots, a_m; spec.$$

525 Here, w is a spatio-temporal window specification, identifying a part of physical
526 space where the values of attributes a_1 to a_m should be measured. The ex-
527 pression *spec* refers to a specification for how the module IM of control should
528 obtain these values.

529 If this object satisfies the type formula $\alpha(x)$, the IcS control follows these
530 steps:

- 531 • It expands the universe of objects within IS by adding the new object o .
- 532 • The IcS control sends a request to the IM to execute the specification *spec*
533 in the physical world.
- 534 • IM initiates a process in which it perceives the values of attributes a_1 to
535 a_m in the specified part of the physical space (defined by w).
- 536 • These values are then stored in the expanded information system IS' as
537 attribute values for the newly created object o .

538 One can observe that the specification of type of information system IS is
539 closely related too specification of a family of admissible changes of IS .

540 Let us consider one more example for illustrating the difference between
541 information granules considered in GrC and c-granules from IGrC. In this ex-
542 ample, information *inf* specifying an intended change of a given information
543 system IS to IS' is related to adding a new attribute to the set of attributes of
544 IS , with values computed according to a given procedure *proc*. If this specifi-
545 cation is admissible for IS by its type then the change of IS to IS' is realized
546 by implementation of the procedure *proc* for each object from IS and taking
547 the computed by the procedure value as the value of attribute for each consid-
548 ered object. In this case, assuming that the realization is not disturbed by the
549 environment one can consider only transformation in the corresponding infor-
550 mational layer without referring to the physical world.

551 Summarizing, we propose the following changes in modeling of information
552 systems in comparison to the Pawlak model:

- 553 • *The Key to Dynamics: Open Information Systems.* We propose a general-
554 ization of Pawlak's information systems into 'open' information systems.
555 These systems are dynamic entities, and the IcS control is responsible for
556 their evolution during computations seeking high-quality approximate so-
557 lutions for problems the IcS needs to solve. Hence, the dynamics of these
558 systems is not defined a priori as it was proposed in papers on dynamic
559 information systems so far (see, *e.g.*, [83, 84, 85]). Pawlak's information
560 systems can be seen as starting points, or "seeds." We need to consider
561 huge spaces of information systems around them. Within these spaces, it
562 is necessary to search for (semi-)optimal information systems (or approx-
563 imation spaces). The relevant reasoning techniques should be developed
564 supporting this search making it i to induce the relevant computational
565 building blocks for cognition, like classifiers or clusters. Furthermore, the
566 IcS control system must be aware that these vast information spaces are
567 dynamic and change over time.
- 568 • *Challenges and Networks.* The intended dynamics may not always be
569 achieved due to unforeseen interactions with the physical environment.
570 Furthermore, the IcS control often deals with multiple interconnected
571 information systems rather than a single one, forming networks of informa-
572 tion systems. These networks can be viewed as networks of c-granules
573 over which computations are generated by control of IcS.

• *System Types and Object and objects in Information Systems.* Each information system has a type that specifies the allowed type of objects in it, in particular those that can be added in updating. The type is typically specified using some properties of fragments of granular computations generated by the IcS. Objects within an information system must be compatible with the system's type. It can be treated as a filter for objects to be stored in information system. Objects in information systems are descriptions of structural objects labeled by specifications of spatio-temporal windows, like bitmaps of images, fragments of time series or their clusters, together with encoded in these descriptions procedures and/or specifications of associations used by control of IcS for computing values of the relevant attributes. The control of IcS is using

- (i) a procedure from the object to compute necessary attribute values for an object using, *e.g.*, information from other information systems and/or
- (ii) a specification of an association from the object with the specified fragment of the physical space; a process is associated with this specification that is realized in the physical world by IM, allowing IcS to perceive, *e.g.*, the desired attribute values and store them in the information system.

Hence, attributes considered in the paper are not necessarily abstract functions by they may be defined by specifications of associations and their realization in the physical world by IM.

The type specification can also include information on how the IcS control can update the information system, *e.g.*, by adding or removing rows or columns. For example, a type might specify a type of spatio-temporal windows, a list of attributes to measure within the fragments of the physical space corresponding to those windows, additional information like measurement timeframes and expected results. Control of IcS is responsible for updating the system with the perceived in physical realization measurement values.

• *Dynamic by Design, Not Random.* These generalized information systems are dynamic, not randomly so. Their evolution is determined by the IcS control's intended dynamics, which can be influenced by interactions with the physical environment. This implies that the information systems in this paper are not purely mathematical objects. Their dynamics are defined by c-granules representing the systems themselves and their interactions with other c-granules, working like physical pointers to specific parts of the physical space. These pointers allow the IcS control to perceive properties of physical objects in those parts and use this information to update the current state of the systems.

This type of modeling is essential for seriously considering issues related to perceiving complex situations in the physical world and making the right deci-

sions about them. We demonstrated that our approach to information systems can be seen as a constructive way to define dynamic approximation spaces. These spaces are changing accordingly to changes of corresponding to them information systems and they can be used to search for computational building blocks for cognition, such as patterns, clusters, or concept approximations (classifiers) as well as their hierarchical structures relevant to problem-solving by the IcS.

Typically, control of IcS deals with a family of information systems generated in the perception of situations. Moreover, the information systems from such families are linked by different relations representing relationships between objects, fragments of the whole information systems. In this way are created networks of information systems. They are examples of more compound c-granules (or information granules), corresponding according to our previous discussion, to families of approximation spaces. Here, it is worthwhile mentioning the relationships with information flow [86, 87] attempting to develop logical foundations for distributed computing. One should also refer here Fuzzy(-Rough) Cognitive Networks (see, *e.g.*, [88, 89, 90, 91]) as well as Federated Learning (see, *e.g.*, [92, 93]) as examples of techniques aiming to create machine learning models with improved performance on distributed datasets (without sacrificing privacy). On the way to create such models many challenges appear concerning, *e.g.*, creating, designing, operationalizing or maintaining distributed systems. One of the challenges is related to developing reasoning methods supporting solving these challenges.

The proposed approach focuses on developing reasoning methods that support the construction of approximate solutions for specified tasks. These methods must consider additional constraints during construction. These constraints can include privacy requirements, limitations on data aggregation due to resource limitations, or adherence to principles expressed in natural language standards (*e.g.*, ISO standards) that may contain complex and vague concepts. Importantly, these reasoning methods should not only analyze pre-constructed solutions but also actively support the construction process itself, working alongside the granular computations generated by IcS. Dialogues with human experts may play a crucial role in this process. Furthermore, at different stages of the IcS computations, solved subproblems can be treated as optimization problems within large families of approximation spaces.

Aggregation and decomposition operations as well as filtration (see, *e.g.*, [74, 94]) of information systems enable us to construct new information systems on the basis of which new relevant c-granules being computational building blocks for comprehension of the perceived situations are discovered.

One of the fundamental issue of information systems under the control of IcS is that they are open to interaction. They are changed by control of IcS. The changes are controlled by reasoning skills of control. We discuss this issue in more detail in the subsequent section.

660 6. Adaptive rough sets

661 In the Pawlak model of rough sets [39, 40, 95] the boundary region of the
662 approximated vague concept is defined as the difference between upper and lower
663 approximation of the concept. Hence, the boundary region is crisp set. However,
664 philosophers argue that the collections of borderline cases creating the boundary
665 region cannot be defined as a crisp set [96]. In the Pawlak model of rough sets,
666 the boundary region is defined relative to given sets of attributes and objects.
667 These sets are represented by information systems [39, 40, 95, 37]. Certainly,
668 when these sets are changing the boundary region is changing too. Hence, it
669 was proposed (see, *e.g.*, [97]) to consider for approximation of vague concepts
670 a process expressing changes in approximations of a given concept according to
671 changes of sets of attributes and objects rather than an approximation defined
672 on the basis of a given a priori information system.

673 From the above discussion it follows that for construction of approximation of
674 concepts we should rather consider dynamic information systems rather than a
675 given a priori information system. As it was already mentioned, in the literature,
676 one can find several proposals of definition of dynamic information systems (see,
677 *e.g.*, [83, 84, 85]). In these proposed approaches the dynamics is treated as given
678 a priori. This is not reflecting requirements for Intelligence Systems (IcS) where
679 information systems are in a sense under control of these systems and they are
680 changing according to rules of control of these systems and interactions with
681 the physical world. This point of view is represented in the approach based on
682 IGrC (see, *e.g.*, [18, 19, 20, 21, 22, 23] and [24, 25]).

683 Control of IcS is responsible for updating and generation of information
684 systems in IcS. However, one should note that the expected changes of IcS
685 planned by their control may be disturbed by interactions with the physical
686 environment. Updating of information systems is often caused by sensory mea-
687 surements. Hence, it is related to interactions with physical objects. Generation
688 of new information systems or decomposition of the existing ones is performed
689 by aggregation or decomposition operations. From this it follows that modeling
690 of control of IcS requires objects composed out of abstract and physical objects.
691 Complex granules (c-granules, for short) are such objects in IGrC.

692 The control of IcS consists of reasoning module playing the fundamental
693 role. The reasoning is performed on networks of c-granules (more compound c-
694 granules). It is aiming to decide which transformation should be performed on
695 the current granular network toward construction of approximate solutions for a
696 given specification of problem to be solved. From the point of view of the rough
697 set approach one can formulate this as the requirement of construction of granule
698 representing the approximate solution belonging to the lower approximation of
699 the concept consisting all solutions of the given problem.

700 6.1. Pawlak's information systems vs Scott's information systems

701 An interesting interpretation of Pawlak's information systems follows from
702 comparison them with the definition of Scott information system [98]. This
703 interpretation may bring some hints in developing reasoning methods for the

control of IcS related to issues concerning dynamics of information systems working under the control of IcS. Hence, we outline this interpretation here.

In [98] the intuition of information systems is presented as follows. Intuitively, an information system is a set of ‘propositions’ that can be made about ‘possible elements’ of the desired domain. The formal definition is as follows.

Definition 5. *An information system is a structure*

$$(D, \Delta, Con, \vdash),$$

where D is a set (the set of data objects or propositions), where Δ is a distinguished member of D (the least informative member), Con is a set of finite subsets of D (the consistent sets of objects), \vdash is a binary relation between members of Con and members of D (the entailment relation for objects).

Concerning Con , the following axioms must be satisfied for all finite subsets $u, v \subseteq D$:

- (i) $u \in Con$, whenever $u \subseteq v \in Con$;
- (ii) $\{X\} \in Con$, whenever $X \in D$; and
- (iii) $u \cup \{X\} \in Con$, whenever $u \vdash X$.

Concerning \vdash , the following axioms must be satisfied for all $u, v \in Con$, and all $X \in D$:

- (iv) $u \vdash \Delta$;
- (v) $u \vdash X$, whenever $X \in u$; and
- (vi) if $v \vdash Y$ for all $Y \in u$ and $u \vdash X$, then $v \vdash X$.

One can interpret an information system defined by Pawlak as a kind of recording information about some perceived situations represented by signatures of objects. Then, this information system represents in a sense a family of consistent sets, represented by signatures of objects, perceived up to a given moment of time. The dynamics of information systems is determined by control of IcS and interactions with the physical world. Hence, instead of a single entailment relation one can propose to learn some hypothetical entailment relations using some idea, *e.g.* from paraconsistent logic [99, 100, 101, 102] in cooperation with experts. One should be aware that it is necessary to consider not only consistent sets but to develop tools which can provide useful conclusions in the case of inconsistent sets. Here, one can refer to the research concerning inconsistent knowledge bases (see, *e.g.* [103]). Some issues concerning the discussed problems already appear in inconsistent decision systems, what was mentioned in Introduction.

Let’s consider the case of Scott information systems, where the entailment relation is assumed to be known upfront (a priori). While the derivation rules used by the control of IcS can often be learned from data (see, *e.g.*, schemes of approximate reasoning in [94]). Moreover, their computational complexity becomes an important factor. Imagine a situation where the current state is represented by information *inf*. The IcS control needs to extract a relevant

744 fragment from a large knowledge base *kb* (represented by an information gran-
745 ule) to infer new information about the situation and accordingly extend *inf*.
746 The efficiency of this process depends heavily on how knowledge is represented
747 in *kb*. It's also worth noting that dealing with inconsistencies (or paraconsis-
748 tencies) in the knowledge base might necessitate dialogues with human experts
749 and reasoning tools for resolving conflicts. In the case of of Scott information
750 systems an important role play maximal consistent sets. In the case of IcS,
751 reasoning is based on consistent (or inconsistent) sets because maximal consis-
752 tent sets usually are not available for IcS, *e.g.*, because of bounds on resources.
753 Moreover, reasoning rules in IcS are realized by transformations of *c*-granules,
754 where their specifications of transformations are represented in informational
755 (abstract) layers and their realization is defined by physical semantics, hence
756 transformations are not purely purely mathematical objects. The realization
757 of transformations in the physical world is not always as predicted by their
758 specifications because of interactions with the environment.

759 **7. Dialogues of IcS with human experts grounded on IGrC in search-** 760 **ing for computational building blocks for cognition: General com-** 761 **ments**

762 In this section, we discuss in more detail issues related to dialogues of IcS
763 with human experts. In particular, our discussion also concerns dialogue systems
764 for Human Computer Interaction (HCI) (see *e.g.*, [104, 105]). IGrC is the basic
765 computing model on which we propose to ground the approach.

766 We have already emphasized in Introduction that for IcS dealing with com-
767 plex phenomena it is not possible to eliminate dialogues with human experts.
768 Among them is the problem that still we do not have enough reliable automatic
769 techniques for common sense reasoning and/or experience based reasoning.

770 The idea of common sense is well expressed in [106]:

771 *We look at the idea of common sense as it exists in humans. We*
772 *make the case that it is tied to knowing certain ordinary things. We*
773 *argue that common sense is the ability to make effective use of this*
774 *knowledge in deciding how to behave and plays a critical role in the*
775 *spectrum of human cognitive capabilities.*

776 One should note that developing robust commonsense reasoning capabili-
777 ties for control of IcS presents several key challenges related to commonsense
778 knowledge. Among them are:

- 779 • Acquisition and representation of commonsense knowledge.
- 780 • Contextual and dynamic nature of commonsense knowledge.
- 781 • Ambiguity and uncertainty in commonsense knowledge.
- 782 • Integration of reasoning module with other components of IcS control
- 783 concerning commonsense knowledge.

- 784 • Explainability and transparency of commonsense reasoning.
- 785 • Scalability and generalization of commonsense knowledge.

786 Addressing these challenges requires a multidisciplinary approach, incorporat-
 787 ing advances in knowledge representation, machine learning, natural language
 788 processing, cognitive science, and other relevant fields.

789 One of the important issue where IcS should cooperate with human experts is
 790 related to decomposition of complex vague concepts. This problem appears with
 791 such vague specifications as necessity to preserve as invariant ‘safeness’ [36] or
 792 provide ‘trustworthiness’ [107] of the system. Decomposition of complex vague
 793 concept appears also during implementation of specifications of transformations
 794 in the physical world. If a specification is to compound for the implementation
 795 module IM of control then it may be necessary to ask a human expert for a help
 796 in decomposition. Lotfi Zadeh suggested [108, 109] that information granulation
 797 plays a key role in implementation of the strategy of divide-and-conquer in
 798 human problem-solving. Often it is necessary to perform such decomposition
 799 several times, through different levels, before it is possible to rich the level
 800 directly implementable in the physical world. The problem of decomposition
 801 of vague specification is also important in hierarchical learning. In particular,
 802 for several real-life projects it was possible to obtain the high quality solutions
 803 using so called ontology approximation based on the rough set approach, where
 804 ontology of vague concepts was acquired through dialogues with experts (*e.g.*,
 805 [36, 48]). The discussed issue of decomposition of complex vague concepts is
 806 also closely related to a cited below challenge formulated by Judea Pearl [110].

807 Another very important issue related to dialogues of IcS with experts is that
 808 the control of IcS should deliver on the basis of accumulated data and knowl-
 809 edge in informational layers of c-granules understandable by human information
 810 supporting experts in making the right decisions. This information can be pro-
 811 vided in natural language, in a graphical form (see, *e.g.*, QMAK project [111])
 812 or using some easily understandable by human expressions.

813 8. Outline of the LITL project findings

814 Foundations based on IGrC for IcS dealing with complex phenomena are
 815 aiming to realize the following general goal, paraphrased to IcS from [112] where
 816 it was formulated for biology:

817 *Tomorrow, I believe, we will use [IcS] to support our decisions in*
 818 *defining our research strategy and specific aims, in managing our ex-*
 819 *periments, in collecting our results, interpreting our data, in incor-*
 820 *porating the findings of others, in disseminating our observations,*
 821 *in extending (generalizing) our experimental observations through*
 822 *exploratory discovery and modeling - in directions completely unan-*
 823 *ticipated*

824 Now, we shortly characterize the LITL project [35] developed by QED com-
 825 pany and present a roadmap for further development dialogues of human experts
 826 with IcS.

827 LITL is aiming to develop an automatic and semi-automatic system for
 828 marking data in large data sets based on machine learning. In particular, LITL
 829 provides methods for:

- 830 • *Few-shot learning*:
 - 831 (i) *Active learning samples selection*: Intelligent samples selection lead-
 832 ing to largest expected model improvements.
 - 833 (ii) *Initial batch selection*: Deterministic, reliable methods for selecting
 834 initial data samples to avoid production quality minimums.
- 835 • *Expert assignment*: Labeling experts matched to the samples based on
 836 their latent competencies.
- 837 • *Expert consensus*: Ground truth estimated based on experts quality even
 838 in case of contrary votes.
- 839 • *Expert quality estimation*: Experts' quality and latent competencies con-
 840 tinuously updated.
- 841 • *New classes identification*: New not yet known classes identified and pointed
 842 out to experts for evaluation.

843 It was already shown that on the road of LITL development the rough set
 844 based methods can be very helpful. In particular:

- 845 • Reduct ensembles can be the basis for fast similarity calculation [113].
- 846 • Reduct ensembles can be quite good models in practice: [63].
- 847 • They may also provide hints about most useful features: [114].
- 848 • It can be extended toward interactive feature selection: [115].

849 There are already in LITL some tools related to selection of queries based
 850 on similarity. Among them are the following:

- 851 • A data case may be worth showing to Subject Matter Expert (SME) if
 852 it is not similar to any cases that were considered in the learning process
 853 up to now.
- 854 • A data case may be worth showing to SME if it is similar to a group of
 855 other cases labeled by that SME up to now, but SME seemed to be quite
 856 uncertain about those cases.
- 857 • A data case may be worth showing to SME if it is similar to a group other
 858 cases that were analyzed by the previous versions of a model that we learn,
 859 but that model seemed to be quite uncertain about those cases.

860 The core concept behind LITL's development supporting construction of
 861 classifiers can be summarized as follows. We begin with a given multi-relational
 862 approximation space, or corresponding to it a decision system, denoted by AS.
 863 Based on AS, LITL constructs a typically large space \mathcal{F}_{AS} of related multi-
 864 relational approximation spaces. Next, an optimization strategy is employed
 865 to search for specific multi-relational approximation spaces within \mathcal{F}_{AS} . These
 866 spaces are chosen because they enable the creation of high-quality classifiers
 867 (according to pre-defined quality measures). These classifiers can be, *e.g.*, in
 868 the form of ensembles of classifiers (see Fig. 3 and [63]). The optimization
 869 process can also be performed by tuning metaparameters of learning algorithms
 870 (see, *e.g.*, [116]).

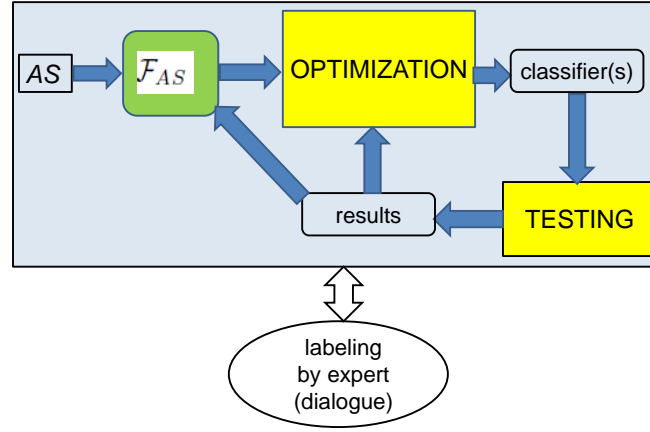


Figure 3: Optimization in the loop with experts for inducing the high quality classifiers.

871 Labeling by experts (see Fig. 3) may concern, in particular suggestions con-
 872 cerning:

- 873 • expressed in natural language new attributes (features) or selection of the
874 relevant objects;
- 875 • discretization or symbolic value grouping;
- 876 • definition of new fuzzy attributes (*e.g.*, based on linguistic variables);
- 877 • aggregation of patterns defined over languages of given attributes;
- 878 • explanation why the decision is incorrect what may help to modify classi-
879 fiers;
- 880 • new languages of attributes (features) in which searching for the relevant
881 attributes should be performed;
- 882 • dealing with missing values.

9. Roadmap for dialogues in IcS

There are several challenges for the further research on dialogues of IcS with human experts. Below we shortly describe examples of them.

The first research direction is related to development of an advanced dialogue interface of the system with users/experts. This interface is making it possible to exchange messages between system and experts in dialogues carried out toward the relevant labeling of objects with compound structural complexity. The model is based in a recently emerging paradigm Interactive Granular Computing (IGrC) (see, e.g., [18, 19, 20, 21, 22, 23] and [24, 25]). In IGrC messages are encoded into informational layers of (complex) granules and the process of sending/receiving messages, treated as information granules, is realized through relevant interactions of these granules. Representation of objects as well as their labels are realized by information granules. For example, objects can represent queries sent by the experts to the system and labels represent messages received from the system. Another example concerns objects in the form of queries sent to a domain knowledge base and labels represent description of parts of these knowledge bases containing the relevant information for the queries. Hence, in this way we consider a generalization of the concept of labeling function from simple one considered before to a higher order labeling function where objects and their labels are information granules with a compound structure. Certainly, such functions should preserve some constraints related to informativeness of labels. Such labeling functions may be of great importance for IcS in their dialogues with experts. For example, labels can indicate the level of risk associated with the current situation compared to the desired goals. They might suggest the need for immediate sensory measurements to gain a clearer understanding. In general, labelers should be aware that successful cooperation with IcS relies on the entire granular computation process performed by IcS, not just a single decision made at a specific point in the computation.

One very interesting area for expert dialogues concerns resolving conflicting opinions between experts and IcS. IcS can leverage relevant conflict resolution methods while engaging in dialogues with experts. For example, consider rule-based object classifiers (see, e.g., [48, 117, 111]). These classifiers may assign conflicting labels to an object based on different rules matching the same object. Through dialogue, experts and the system can gather arguments *for* and *against* each decision, ultimately aiming to reach a consensus. Expert insights can further enhance the system's methods. For instance, a medical expert might highlight a high risk of a rare, undiagnosed disease in a patient, even if the current rule-based classifier data doesn't reflect it. In this scenario, expert labeling can serve as a form of critique, suggesting modifications to the system's classification process. This example demonstrates that labeling functions can very much vary in complexity and purpose.

The critical challenge for the further development of IcS is related to the development of reasoning methods that support the effective perception of relevant data for inducing their models. These methods should aid the control of IcS in making decisions concerning *what*, *when*, *how*, and *where* to perceive data

about the analyzed situations. Moreover, they should support constructions of representations of perceived data by information systems, their networks and making aggregations of them. When IcS are dealing with complex phenomena, unavoidable dialogues between the IS and human experts should take place to provide the IcS with satisfactory information for making the right decisions. The importance of data governance is emphasized in the literature about IcS [118] especially for companies following data driven business.

It's important to highlight a key difference between the approach based on mathematical logic and the one discussed here. Mathematical logic focuses on pre-defined relational structures (models) and a language of formulas built upon them. Examples include the relations of semantic consequence and syntactic consequence. This approach then studies, *e.g.*, the relationships between these entities. In contrast, the approach discussed here aims to learn (discover), at least partially, both the relations and the formulas (attributes) directly from data. This data is perceived from relevant fragments of the physical space pointed by the attention module of the IcS control and this process is supported by reasoning techniques of this module. Moreover, one should take into account that the relevant data and their localization in the physical space are changing with time. Hence, the control of IcS should be aware of continuous supporting of searching for the relevant data by the reasoning techniques.

One should note that nowadays the dialogues with experts can be supported by chatbots [119]. For example, after labeling cases by expert the system could initiate dialogues with chatbots aiming to provide for IcS better understanding concepts and relations between them used in this labeling. This may be used in decomposition of complex vague concepts or, in a more general sense, description of the perceived situations up to the level directly realizable in the physical world.

One of the crucial problem in development of technology supporting dialogues between system and experts is related to developing of languages over which information granules are defined. It is well defined by Judea Pearl, the Turing award winner [110]:

Traditional statistics is strong in devising ways of describing data and inferring distributional parameters from sample. Causal inference requires two additional ingredients:

- *a science-friendly language for articulating causal knowledge, and*
- *a mathematical machinery for processing that knowledge, combining it with data and drawing new causal conclusions about a phenomenon.*

An important argument justifying the use of IGrC as the basic computing model is that this computing model is especially relevant for applications where interactions between systems, experts as well as other different hardware tools such as computers, cellular phones, robots, sensors and/or actuators are important. Hence, this model is relevant for applications concerning Internet of

972 Things (IoT) or Cyber Physical Systems (see, *e.g.*, [92, 120, 121]).

973 One more important aspect of the discussed above interfaces between system
974 and experts is related to the paradigms like Human-Centered AI or Human-in-
975 the-Loop ML [3, 4]. In the interfaces of IcS under development we concentrate
976 on developing technology helping experts to perform their experience based rea-
977 soning rather than to eliminate them from the loop. The main reason behind this
978 is that we do not have yet satisfactory formal reasoning tools making it possible
979 to substitute the experts in tasks related to such reasoning. For example, we
980 work on tools for delivering to experts proper visualization of objects or sets of
981 objects. Moreover, we are working on developing tools which can provide ex-
982 perts with information about the risk degree concerning the relevance of labels
983 (*e.g.*, decisions) assigned to objects. The degrees are estimated by the system
984 and provided for experts. One can cite here the opinion of Melanie Mitchell
985 [6, 122] about analogy based reasoning belonging to the experience based rea-
986 soning domain:

987 *The quest for machines that can make abstractions and analo-*
988 *gies is as old as the AI field itself, but the problem remains almost*
989 *completely open.*

990 Let us also note the importance of the trustworthiness [107] requirement for
991 IcS. One should also consider this in the context of interfaces of IcS related to
992 dialogues with human experts. Trustworthiness covers accuracy, explainabil-
993 ity and interpretability, privacy, reliability, robustness, safety, and security or
994 resilience to attacks and ensure that bias is mitigated.

995 Moreover, developing and using AI in ways that are ethical, reduce bias,
996 promote fairness, and protect privacy is essential for fostering a positive effect
997 on society. Hence, in the design of interfaces of IcS with experts one should take
998 into account the necessity of developing reasoning tools for interfaces helping
999 intelligent systems to (i) preserve different sorts of invariants specified by com-
1000 plex vague concepts related to the above mentioned issues and (ii) multi-criteria
1001 optimization.

1002 Let us summarize our discussion as follows.

1003 One key challenge is ensuring effective communication and mutual under-
1004 standing between IcS and the human experts. IcS systems are built on advanced
1005 computational models and frameworks like the IGrC model, which may not be
1006 intuitively accessible to human domain experts. Bridging this gap in techni-
1007 cal knowledge and establishing a common language for productive dialogue is
1008 crucial.

1009 Another challenge is handling the inherent uncertainty and ambiguity that
1010 can arise in human-IcS interactions. Human experts may express themselves
1011 using imprecise, context-dependent language, while IcS systems are designed
1012 to operate on more formal, structured data. Developing robust mechanisms to
1013 interpret and translate between these modes of communication is essential.

1014 The dynamic and iterative nature of the dialogues also poses challenges.
1015 As the human experts provide feedback and new information, the IcS needs
1016 to be able to quickly update its reasoning, adapt its responses, and maintain

1017 coherence throughout the conversation. Balancing responsiveness with stability
1018 is important for building trust and productive collaboration.

1019 Additionally, there are challenges in ensuring the transparency and inter-
1020 pretability of the IcS’s decision-making processes. Human experts will likely
1021 want to understand the reasoning behind the system’s recommendations and
1022 approximate solutions. Providing appropriate explanations and justifications is
1023 crucial for gaining user acceptance and buy-in.

1024 Finally, the dialogues must be designed to leverage the complementary strengths
1025 of humans and intelligent systems. Striking the right balance between human
1026 expertise and IcS capabilities, and seamlessly integrating them, is a key chal-
1027 lenge in realizing the full potential of these human-IcS collaborations.

1028 Designing the IcS system to better interpret and respond to the nuanced lan-
1029 guage used by human experts involves several key issues and challenges showing
1030 that the architecture of interfaces of IcS for interaction with human experts
1031 requires development of numerous advanced modules based on advanced rea-
1032 soning techniques. Among them are, besides of already discussed modules of
1033 the IcS control, modules for: (i) natural language processing (NLP) capabili-
1034 ties, (ii) knowledge representation and reasoning, (iii) interactive clarification
1035 mechanisms, (iv) explainable AI, (v) continuous learning and adaptation, (vi)
1036 multimodal interaction.

1037 By employing these modules and designing for them the relevant reasoning
1038 strategies, the IcS system can become increasingly adapt at interpreting and
1039 responding to the nuanced language used by human experts, leading to more ef-
1040 fective and productive dialogues. Overall, the dialogues between IcS and human
1041 experts require careful consideration of technical, cognitive, and social factors
1042 to enable effective and fruitful exchanges that drive meaningful problem-solving
1043 and decision-making. The IGrC model plays in this the crucial role.

1044 One should also note that the IcS should handle the ambiguity and uncer-
1045 tainty inherent in human expert language providing solutions for several key
1046 challenges related to: (i) ambiguity in natural language, (ii) imprecision and
1047 vagueness, (iii) incomplete or inconsistent information, (iv) contextual depen-
1048 dency, (v) cognitive biases and heuristics, (vi) dynamic adaptation. To address
1049 these challenges, the IcS design may need to incorporate advanced techniques
1050 from areas such as rough-fuzzy based reasoning, probabilistic reasoning, abduc-
1051 tive inference, contextual modeling, and interactive learning. A combination
1052 of these approaches can help the system navigate the inherent ambiguity and
1053 uncertainty present in human expert language, leading to more effective and
1054 productive dialogues. By combining dynamic knowledge representation, con-
1055 textual reasoning, and interactive feedback, the IcS system can navigate the
1056 inherent ambiguity and uncertainty present in human expert language, leading
1057 to more accurate interpretations and more productive dialogues.

1058 Moreover, IcS should employ several key techniques to engage in interactive
1059 clarification and feedback with the human expert, helping to resolve ambiguities
1060 and uncertainties in their language by: (i) clarifying questions, (ii) paraphras-
1061 ing and summarization, (iii) highlighting inconsistencies or contradictions, (iv)
1062 iterative refinement, (v) explanation and transparency. By employing these

1063 interactive clarification techniques, the IcS system can engage in a more dy-
 1064 namic and collaborative dialogue with the human expert, ultimately leading to
 1065 a more accurate and meaningful understanding of the expert’s language and the
 1066 problem at hand.

1067 From our discussion, it becomes clear that for the further development of
 1068 IcS, it is necessary to synchronize many domains that have been developed sepa-
 1069 rately so far. These domains include a proper computing model, perception and
 1070 action, knowledge representation, reasoning under uncertainty, natural language
 1071 processing (NLP), and dialogues of IcS with human experts and chatbots.

1072 There are several challenges on this path, such as those related to the ‘white
 1073 spots’ in reasoning methods. In other words, there are areas within the reasoning
 1074 methods that have not been fully explored or addressed yet.

1075 To summarize, the key points are:

- 1076 • Synchronizing various domains for the development of IcS.
- 1077 • These domains include computing model, perception, action, knowledge
 1078 representation, reasoning under uncertainty, NLP, and dialogues as well
 1079 as challenges related to ‘white spots’ in reasoning methods.

1080 10. Perspectives of rough sets in IcS

1081 In this section, we discuss and summarize shortly perspectives of rough sets
 1082 in the framework of IcS.

1083 In Fig. 4 is presented a context in which rough sets should be considered in
 1084 IcS.

1085 In the context of Figure 4, the rough set approach departs from traditional
 1086 methods that rely on a single information or decision system (data table). In-
 1087 stead, it utilizes perceived data sets with expert input. These data sets are
 1088 used to create multiple multi-relational approximation spaces, denoted as AS_1 ,
 1089 \dots , AS_k , each corresponding to a distinct information or decision system. Var-
 1090 ious techniques are then applied to these spaces to generate a family of multi-
 1091 relational approximation spaces, denoted as $\mathcal{F}_{AS_1, \dots, AS_k}$. This family serves as
 1092 the basis for optimization algorithms searching for high-quality complex games.

1093 It’s important to note that the optimization process involves aggregation and
 1094 de-aggregation, which correspond to granulation and de-granulation of the un-
 1095 derlying information and decision systems, respectively. This process is crucial
 1096 for identifying relevant multi-relational approximation spaces. As Zadeh previ-
 1097 ously emphasized in his proposal on information granulation, ongoing dialogue
 1098 with experts remains essential.

1099 Furthermore, unlike traditional approaches that approximate a single con-
 1100 cept, our method aims to construct a family of concepts in the learning phase
 1101 of complex games. These concepts are labeled by specifications of transforma-
 1102 tions, which represent the specifications of actions. During testing, the quality
 1103 of the discovered complex games is evaluated using application-specific quality
 1104 measures. Additionally, based on the testing results, the games are adapted.

ROUGH SETS IN IcS

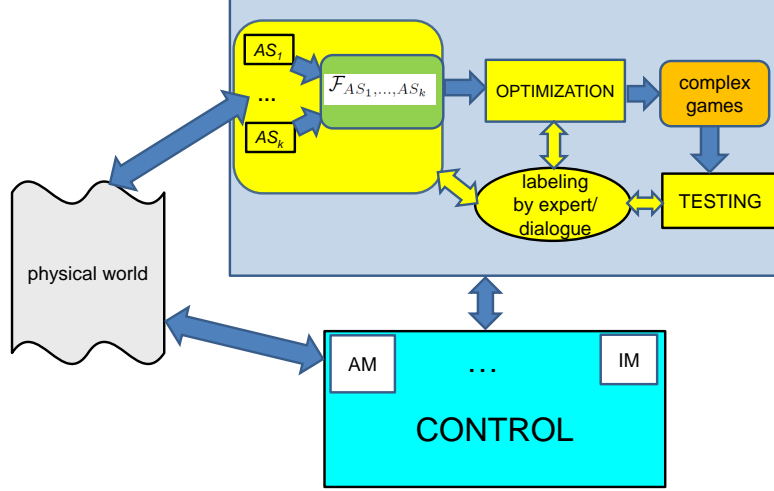


Figure 4: Rough sets in IcS (AM-attention module, IM-implementational module).

1105 The attention module (AM), supported by relevant reasoning techniques and
 1106 expert collaboration, empowers the intelligent control system (IcS) to acquire
 1107 new data sets. This allows for more efficient adaptation.

1108 Summarizing:

- 1109 • The control mechanism of IcS based on the Rough Set Theory framework,
 1110 aims to learn complex games. This allows IcS to generate computations
 1111 over granular networks leading to high-quality approximate solutions.
- 1112 • The control system, aided by an attention module (AM), continuously
 1113 searches for relevant datasets represented in multi-relational approxima-
 1114 tion spaces AS_1, \dots, AS_k . The AM is leveraging advanced reasoning tech-
 1115 niques in collaboration with domain experts.
- 1116 • These approximation spaces can be extended, in cooperation with experts,
 1117 into a large family of multi-relational approximation spaces $\mathcal{F}_{AS_1, \dots, AS_k}$.
 1118 The system then performs optimization to identify high-quality complex
 1119 games.
- 1120 • These complex games are adaptively modified based on observed changes
 1121 in their performance. As previously discussed, complex games consist of
 1122 sets of rules. The predecessors of these rules are classifiers for often com-
 1123 plex and imprecise concepts, while the successors specify transformations

1124 to be applied to granular networks when a rule is chosen for execution by
1125 the IcS control. One should note that IM may require to make multi-level
1126 decomposition of the specification of transformation to be realized before
1127 it can be directly realized in the physical world.

- 1128 • The universes of objects of considered information (decision) systems are
1129 formed by the solutions to the problem IcS is trying to solve, and the
1130 concepts being approximated within this universe correspond to different
1131 quality layers of these solutions. Importantly, in many cases, IcS needs to
1132 generate the granular computation leading to high-quality solutions even
1133 when no known examples of such solutions exist and only some negative
1134 examples are available. This is the case when, *e.g.*, IcS is searching for new
1135 chemical compounds with some specified properties. The success of this
1136 generation process heavily relies on the reasoning techniques supporting
1137 the IcS control. The quality of the generated solution, determined by
1138 the quality of the used complex game, often depends on the behavior of
1139 this complex game over the entire generated granular computation, not
1140 its final state only.

1141 In summary, this approach highlights that approximation problems in IcS
1142 are significantly more complex than those typically encountered in rough set
1143 applications, so far. The success of the control system heavily depends on the
1144 quality of both reasoning techniques and the dialogue with domain experts.

1145 Our research explores new directions for applying the generalized rough set
1146 approach to IcS. This work builds upon the IGrC model and leverages exist-
1147 ing partial results from various fields (including multi-agent systems, perception
1148 and action, machine learning, natural language processing, federated learning,
1149 cognitive networks, smart cities, cyber-physical systems, complex adaptive sys-
1150 tems etc.) by putting them into sync. We also emphasized the fact that IcS
1151 are dealing with complex phenomena in the physical world what requires a new
1152 kind of modeling for solving problems with the design and analysis of IcS. It
1153 was pointed out that dialogues with domain experts are unavoidable for IcS due
1154 to the fact that still we do not have satisfactory formal reasoning techniques
1155 making it possible to deal to a satisfactory degree with commonsense reasoning
1156 or experience based reasoning. The presented comprehensive approach has the
1157 potential to establish a solid foundation for the design and analysis of IcS.

1158 11. Conclusions

1159 We proposed the IGrC model as the fundamental computing model for IcS.
1160 Such systems aim to deliver information relevant for human experts helping
1161 them to make the right decisions. The rough set framework relevant for IcS is
1162 discussed. The crucial role of dynamic information systems in this approach is
1163 explored. Their dynamic behavior is modeled by the control of IcS.

1164 The control of IcS aims to generate computations over the basic objects of
1165 IGrC, called c-granules (or networks of them), such that high-quality approxi-

mate solutions to the problems considered by IcS are constructed along these computations.

We emphasize the essential role of dialogues between human experts and IcS as an integral component of IcS behavior. Some comments on reasoning techniques supporting the construction of approximate solutions, as well as computational building blocks for cognition, are included. Several challenges, especially for the dialogues between IcS and human experts, are also included.

In our next steps, we aim to establish the groundwork for c-granule societies, focusing on how these societies can achieve distributed control and self-organization.

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