ZBIORY PRZYBLIŻONE: OD MODELU PROFESORA ZDZISŁAWA PAWLAKA DO MODELU W INTERAKCYJNYCH OBLICZENIACH GRANULARNYCH

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Komitet Informatyki PAN, Warszawa, 29.11.2023

To
Professors
Helena Rasiowa
and
Zdzisław Pawlak
in memoriam

AGENDA

- Rough sets (RS)
  - Basic model
  - Examples of
    - generalisations
    - combinations with other approaches
    - relationships with other approaches
    - applications
- Motivations for development of a new computing model for Intelligent Systems (IS's) based on Interactive Granular Computing (IGrC)
- IGrC preliminaries
  - (networks of) complex granules (c-granules)
  - control of c-granule
  - dynamics of c-granules and perception
- Rough sets in IGrC
- Summary

RS MODEL OF PROFESSOR ZDZISŁAW PAWLAK

ROUGH SETS

Pawlak, Z.: Rough sets. International Journal of Computer and Information Sciences 11 (1982)

Pawlak, Z.: Rough sets. Theoretical Aspects of Reasoning About Data. Kluwer (1991)

After 40 years: many thousands of papers http://rsds.ur.edu.pl

UNCERTAINTY IN OBJECT PERCEPTION INDISCERNIBILITY RELATIONS

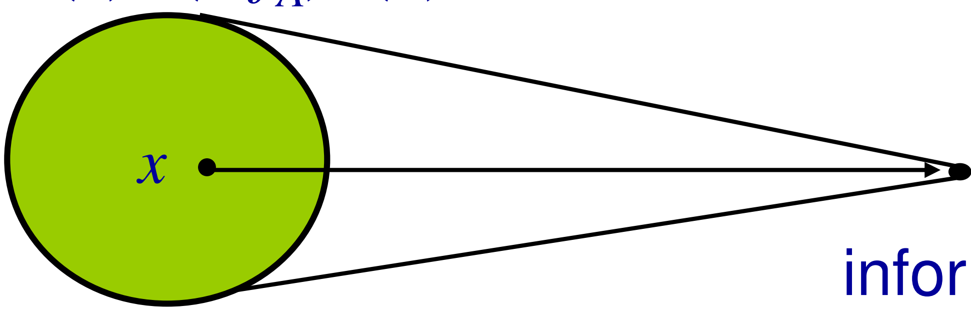
GIVEN information system (data table)

$IS = (U, A)$

$U = \{x_1, \ldots, x_n\},\ A = \{a_1, \ldots, a_m\}$

	a_1	a_2	...	a_m
x_1	v_1	v_2	...	v_m
	...	...	...	...

$N(x) = (Inf_A)^{-1}(u)$



$u = Inf_A(x)$

information signature of $\boldsymbol{x}$

neighborhood of x

elementary granule

$xIND(A)y \ \ iff \ \ Inf_A(x) = Inf_A(y)$

τ

$IND(B) \ \ for \ B \subseteq A$

$[x]_{IND(B)} = [x]_B = \{y \in U : xIND(B)y\}$

tolerance or similarity

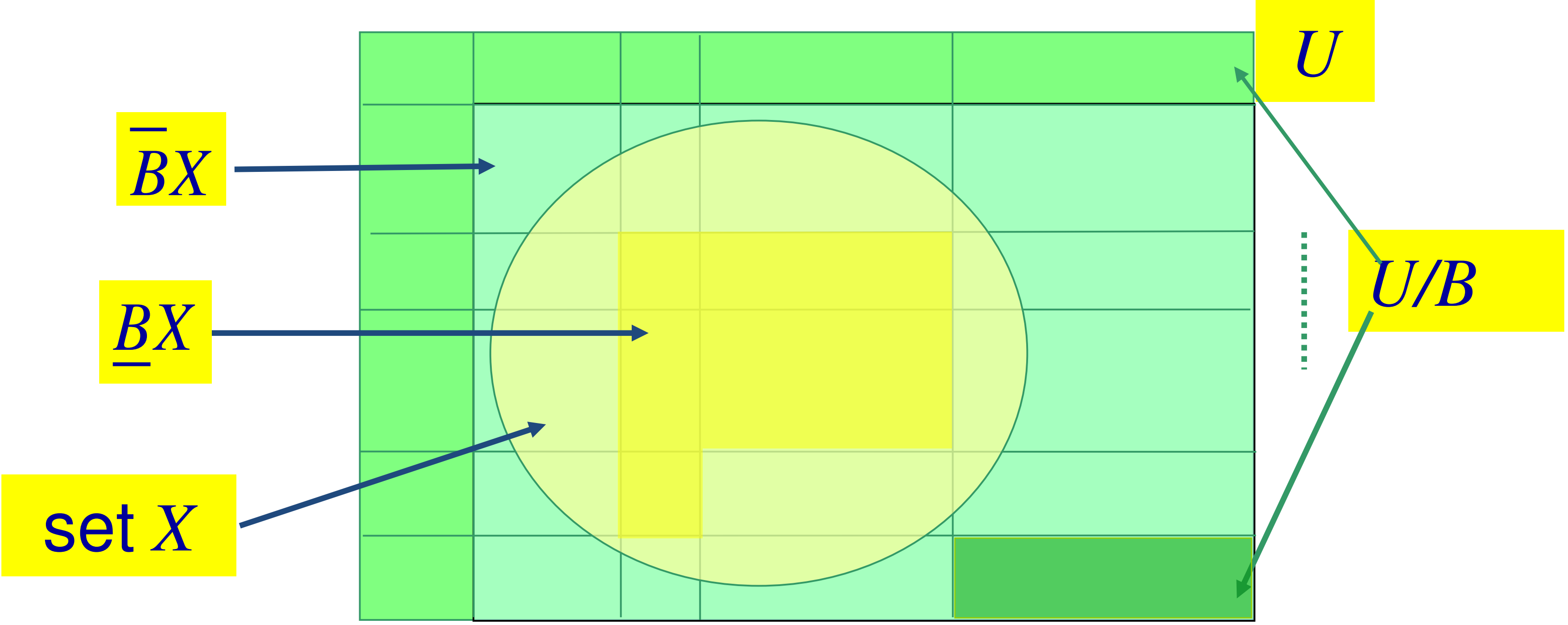
$U / B = \{[x]_B : x \in U\}$

LOWER AND UPPER APROXIMATION

$$X \subseteq U, \; B \subseteq A$$

$$\underline{B}X = \cup \{Y \in U/B : Y \subseteq X\}$$

$$\overline{B}X = \cup \{Y \in U/B : Y \cap X \neq 0\}$$



BOUNDARY REGION

$$BN_B(X) = \overline{B}X \setminus \underline{B}X$$

GENERALIZATIONS
OF
ROUGH SETs

GENERALIZATIONS OF ROUGH SETS

- Similarity (tolerance) Based Rough Set Approach;
- Binary Relation Based Rough Sets;
- Neighborhood and Covering Rough Set Approach;
- Dominance Based Rough Set Approach;
- Probabilistic Rough Set Approach and its probabilistic extension called Variable Consistency Dominance Based Rough Set Approaches;
- Parameterized Rough Sets Based on Bayesian Confirmation Measures;
- Stochastic Rough Set Approach;
- Generalizations of Rough Set Approximation Operations;
- Hybridization of Rough Sets and Fuzzy Sets;
- Rough Sets on Abstract Algebraic Structures (e.g., lattices);
- …

J. Kacprzyk, W. Pedrycz (eds.), Handbook of Computational Intelligence, Springer, 2015 (part on rough sets).

UNCERTAINTY IN SELECTION (DISCOVERY) OF RELEVANT APPROXIMATION SPACE

A. Skowron, J. Stepaniuk, Generalized Approximation Spaces 1994

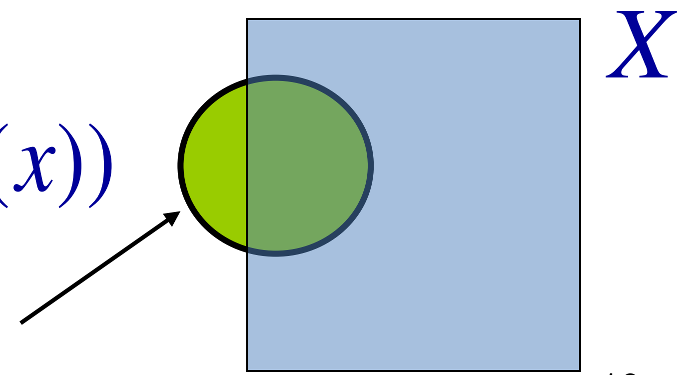
$$AS = (U, N, \nu)$$

$$N : U \rightarrow P(U)$$ neighborhood function

$$\nu : P(U) \times P(U) \rightarrow [0,1]$$ rough inclusion

partial function

$$x \rightarrow Inf(x) \rightarrow N(x) = Inf^{-1}(Inf(x))$$



neighborhood of x

APPROXIMATION SPACE

$$AS = (U, N, \nu)$$

$$LOW(AS, X) = \{x \in U : \nu(N(x), X) = 1\}$$

$$UPP(AS, X) = \{x \in U : \nu(N(x), X) > 0\}$$

uncertainty in membership: degree of membership of *x* into *X*

ROUGH MEREOLOGY

MEREOLOGY

St. LEŚNIEWSKI (1916)

x is_a_ part_of y

ROUGH MEREOLOGY

L. Polkowski and A. Skowron (1994-…)

x is_a_ part_of y in a degree

L. Polkowski, A. Skowron, Rough mereology, ISMIS'94, LNAI 869, Springer, 1994, 85-94

L. Polkowski, Reasonng by parts: An outline of rough mereology, Springer 2011

REASONING: EXAMPLE (induction, conflict resolution)

$$x \in U^* \setminus U$$
$$Ind_A \subseteq U^* \times U^*$$

$$[x]_{Ind_A} \cap U \neq \emptyset$$

$$d(x) = d(x_0)$$
$$for\ some\ x_0 \in [x]_{Ind_A} \cap U$$

$$[x]_{Ind_A} \cap U = \emptyset$$

--- similarity

--- reducts

--- rules

--- conflict resolution

…

ROUGH SETS
AND
VAGUE CONCEPTS

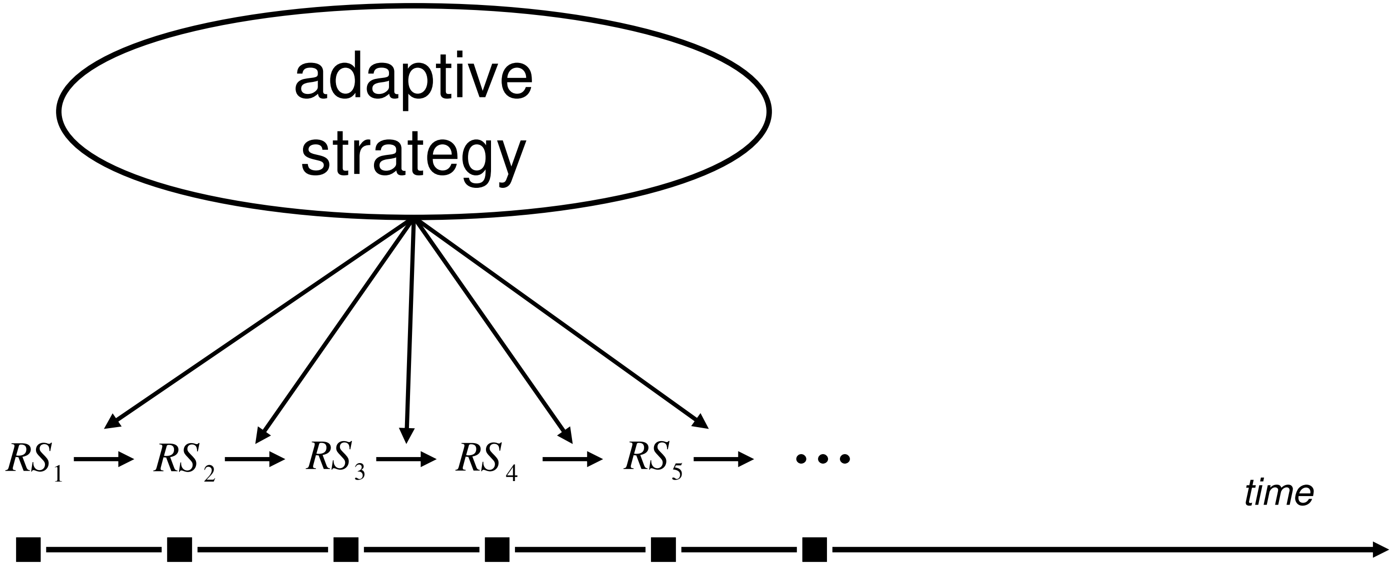
VAGUENESS IN PHILOSOPHY

Discussion on vague (imprecise) concepts includes the following :

1. The presence of borderline cases.
2. **Boundary regions of vague concepts are not crisp.**
3. Vague concepts are susceptible to sorites paradoxes.

Keefe, R. (2000) Theories of Vagueness. Cambridge Studies in Philosophy, Cambridge, UK)

ROUGH SETS AND VAGUE CONCEPTS
ADAPTIVE ROUGH SETS



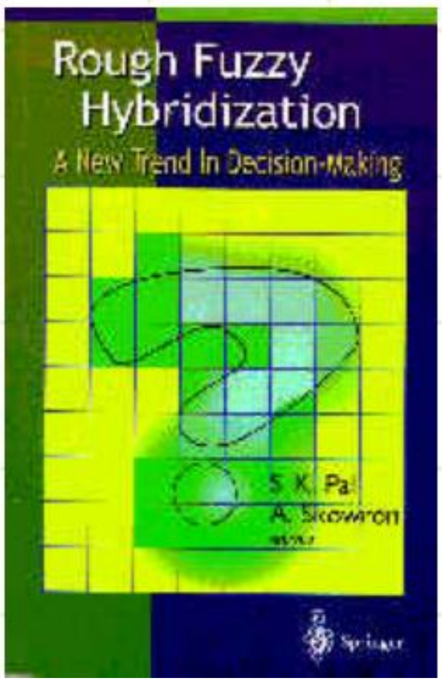
Boundary regions of vague concepts are not crisp
ADAPTIVE ROUGH SETS

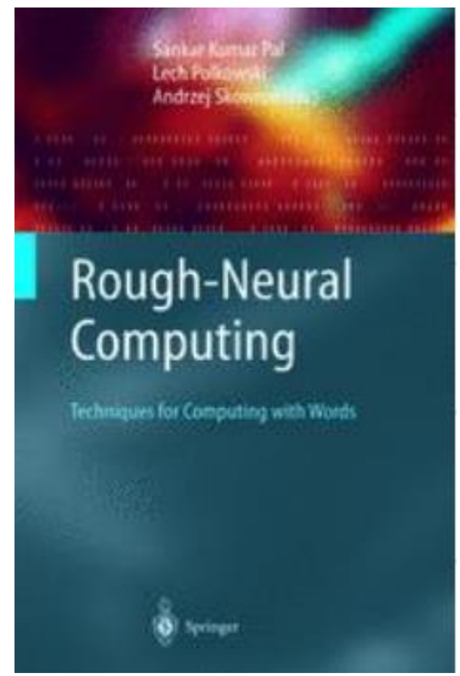
COMBINATIONS
OF
ROUGH SETS
WITH
OTHER APPROACHES

COMBINATIONS OF ROUGH SETS WITH OTHER APPROACHES

- FUZZY SETS
- NEURAL NETWORKS
- GENETIC ALGORITHMS AND EVOLUTIONARY PROGRAMMING
- STATISTICS
- GRANULAR COMPUTING
- WAVELETS, KERNEL FUNCTIONS, CASE-BASED REASONING, EM METHOD, INDEPENDENT COMPONENT ANALYSIS, PRINCIPAL COMPONENT ANALYSIS
- ...

COMBINATION OF ROUGH SETS AND FUZZY SETS

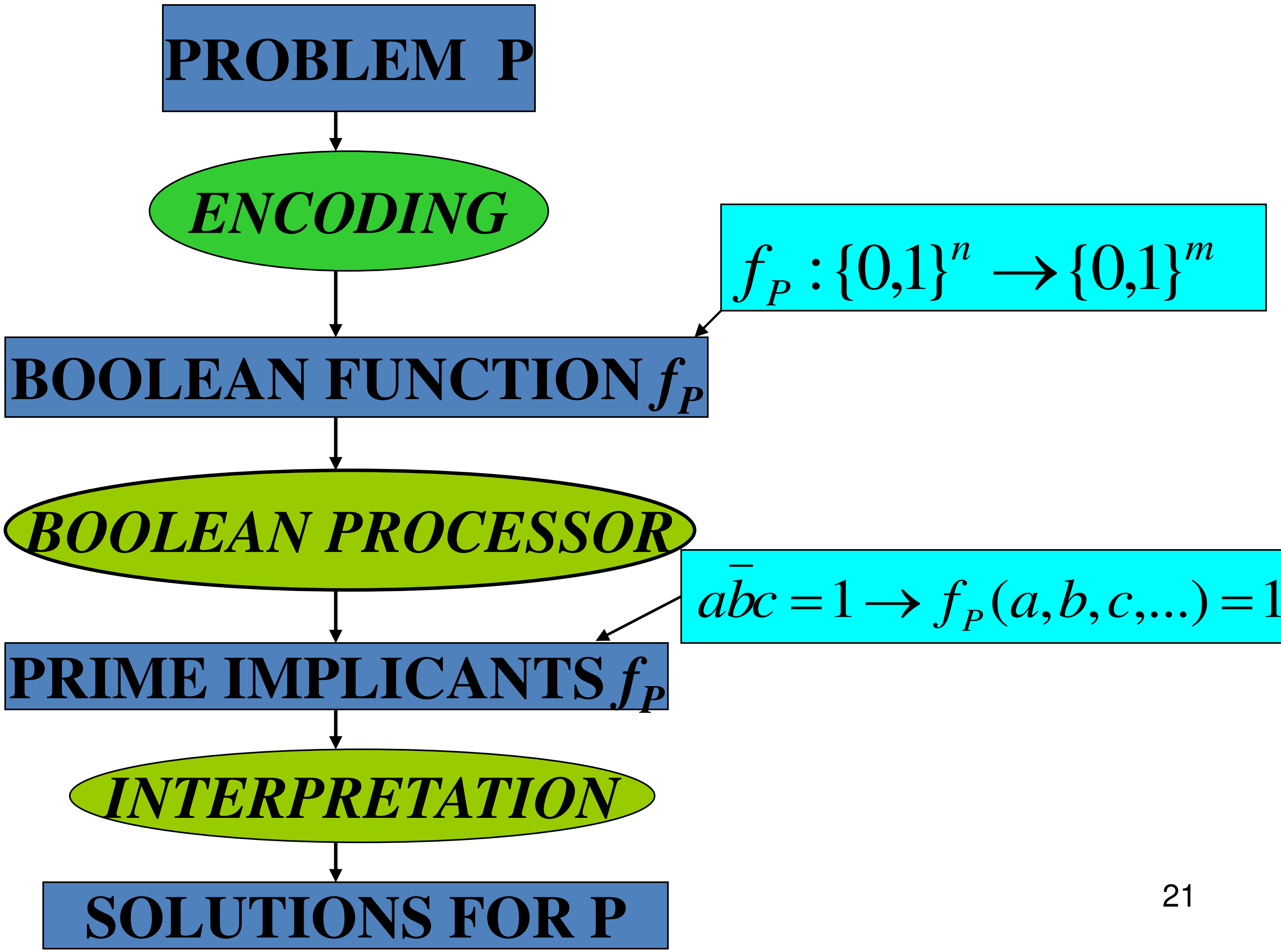




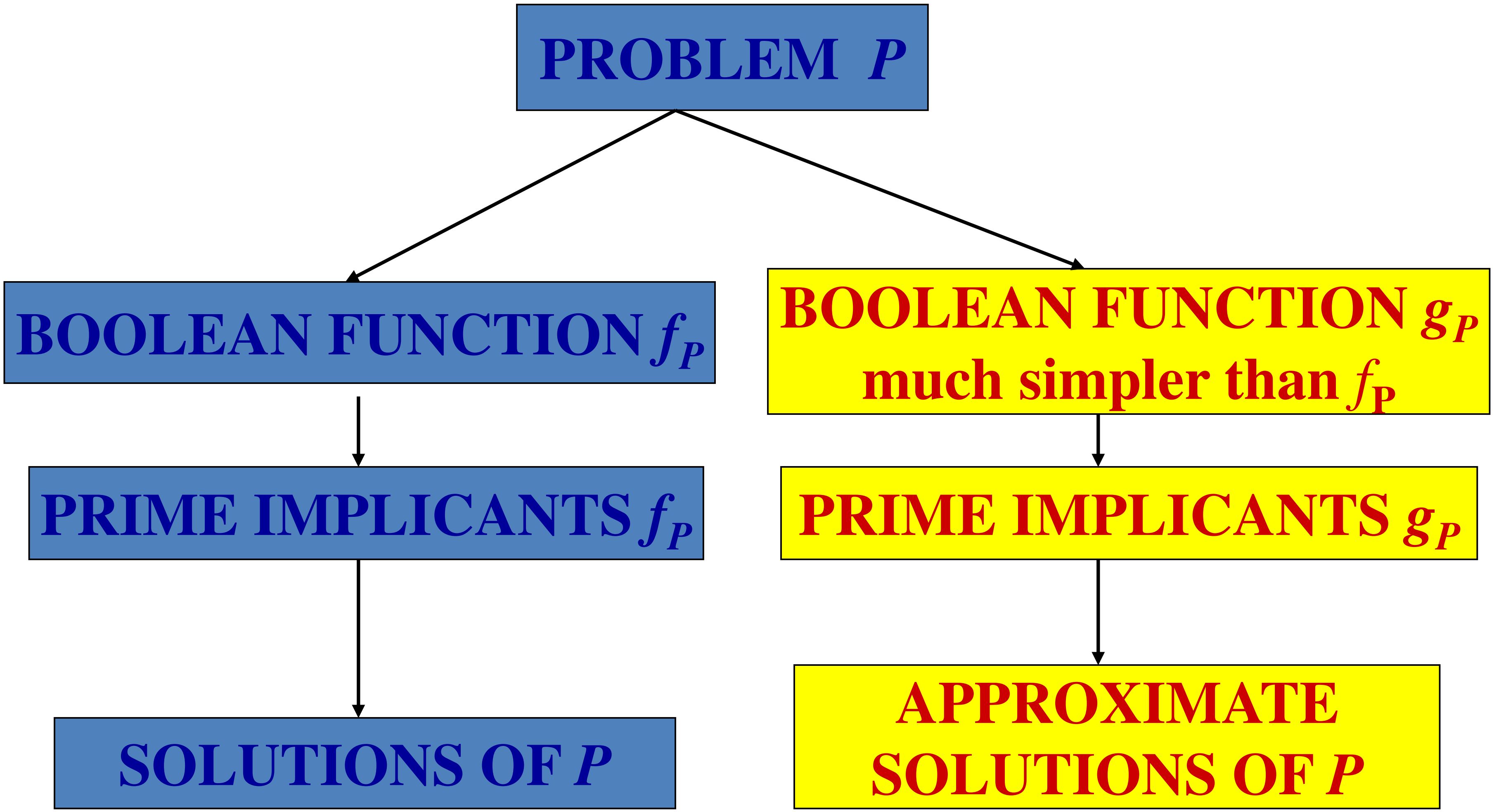
RELATIONSHIPS OF ROUGH SETS WITH BOOLEAN REASONING

BOOLEAN REASONING

George Boole (1815-1864)



APPROXIMATE BOOLEAN REASONING



BOOLEAN REASONING

- **Rough Sets and Boolean Reasoning**
  - Reducts in information systems
  - Decision reducts
  - Local reducts relative to objects
  - Discretization
  - Symbolic value grouping
  - Approximate reducts and association rules

BOOLEAN REASONING

DISCERNIBILITY CONSTRAINTS
TO BE PRESERVED
CAN BE ENCODED BY MEANS OF
BOOLEAN FUNCTIONS
RELEVANT
FOR BOOLEAN REASONING

REDUCTS IN *IS*

$$IS = (U, A)$$

$$\downarrow$$

$$Discernibility\ matrix$$

$$M(IS) = (c_{ij})_{n \times n} : c_{ij} = \{a \in A : a(x_i) \neq a(x_j)\}$$

$$\downarrow$$

$$Discernibility\ function$$

$$f_{IS}(a_1, \ldots, a_m) = \wedge\{\vee c_{ij} : 1 \leq i < j \leq n, c_{ij} \neq \emptyset\}$$

$$\downarrow$$

$$a_{i_1} \wedge \ldots \wedge a_{i_k}\ is\ a\ prime\ implicant\ of\ f_{IS}$$

$$iff\ \{a_{i_1}, \ldots, a_{i_k}\} \in RED(IS)$$

REDUCTS IN *IS*

		x_i	
	...		...
x_j		a, b, c	
	...	c, e	...

$$(a \vee b \vee c) \wedge (c \vee e) \wedge \ldots$$

$$(ae \vee be \vee c) \wedge (\ldots) \wedge \ldots$$

SCALABILITY

- INFOBRIGHT
- USING SIMPLE STATISTICS OF DATA SETS FOR COMPUTING RELEVANT APPROXIMATE INFORMATION ABOUT DISCERNIBILITY (MATRICES) FUNCTIONS
- MapReduce + FPGA

RELATIONSHIPS OF RS WITH OTHER APPROACHES

RELATIONSHIPS OF RS WITH DEMPSTER-SHAFER THEORY

DEMPSTER-SHAFER THEORY (evidence theory)

$$\Theta - \textit{frame of discernment (set of decisions)}$$

$$m : P(\Theta) \to [0,1] \;\; \textit{mass function}$$

$$m(\varnothing) = 0$$

$$\sum_{\Delta \subseteq \Theta} m(\Delta) = 1$$

$$\boxed{\begin{aligned} Bel(\Delta) &= \sum_{\Gamma \subseteq \Delta} m(\Gamma) \;\; \textit{belief function} \\ Pl(\Delta) &= \sum_{\Gamma \cap \Delta \neq \varnothing} m(\Gamma) \;\; \textit{plausibility function} \end{aligned}}$$

G. Shafer, Mathematical theory of evidence, Princeton University Press, 1976

RS & DEMPSTER-SHAFER THEORY

dec. system: DT=(U,A,d),

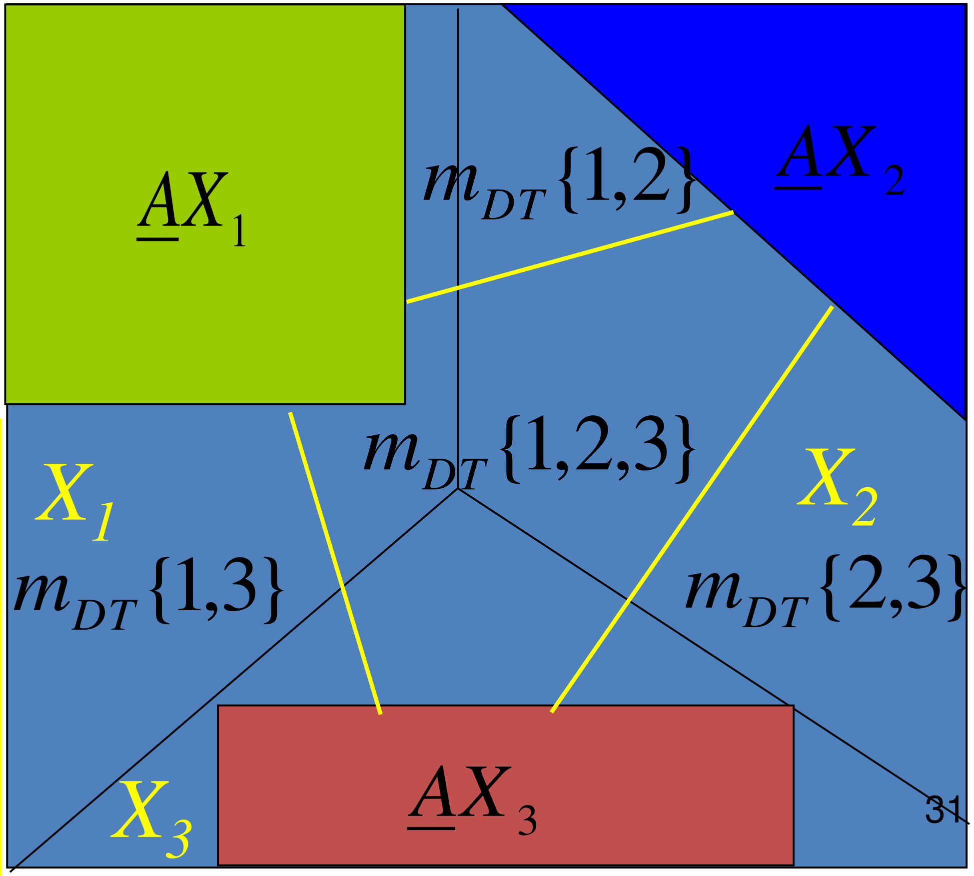
gen.decision: $\delta_A(x) = d([x]_A)$

$$m_{DT}(\Delta) = \frac{\left|\{x \in U : \partial_A(x) = \Delta\}\right|}{|U|}$$

$$\Delta \subseteq \{1,2,3\}$$

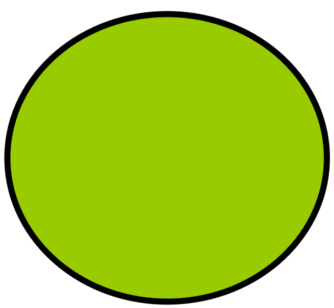
$$Bel_{DT}\{1,2\} = \sum_{\Gamma \subseteq \{1,2\}} m_{DT}(\Gamma) = \frac{\left|\underline{A}(X_1 \cup X_2)\right|}{|U|}$$

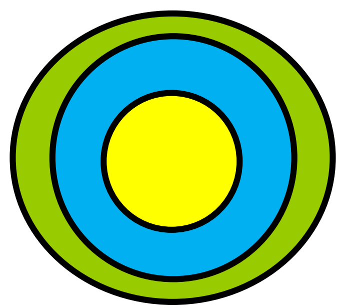
$$Pl_{DT}\{1,2\} = \sum_{\Gamma \cap \{1,2\} \neq \emptyset} m_{DT}(\Gamma) = \frac{\left|\overline{A}(X_1 \cup X_2)\right|}{|U|}$$

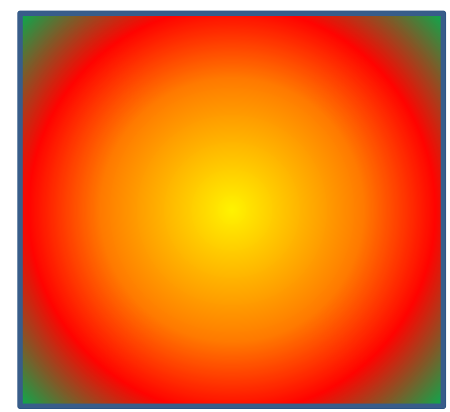


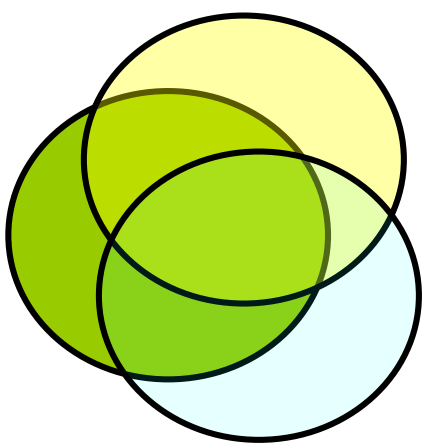
RS
&
GRANULAR COMPUTING (GrC)

ELEMENTARY GRANULES + OPERATIONS ON GRANULES = CALCULI OF GRANULES









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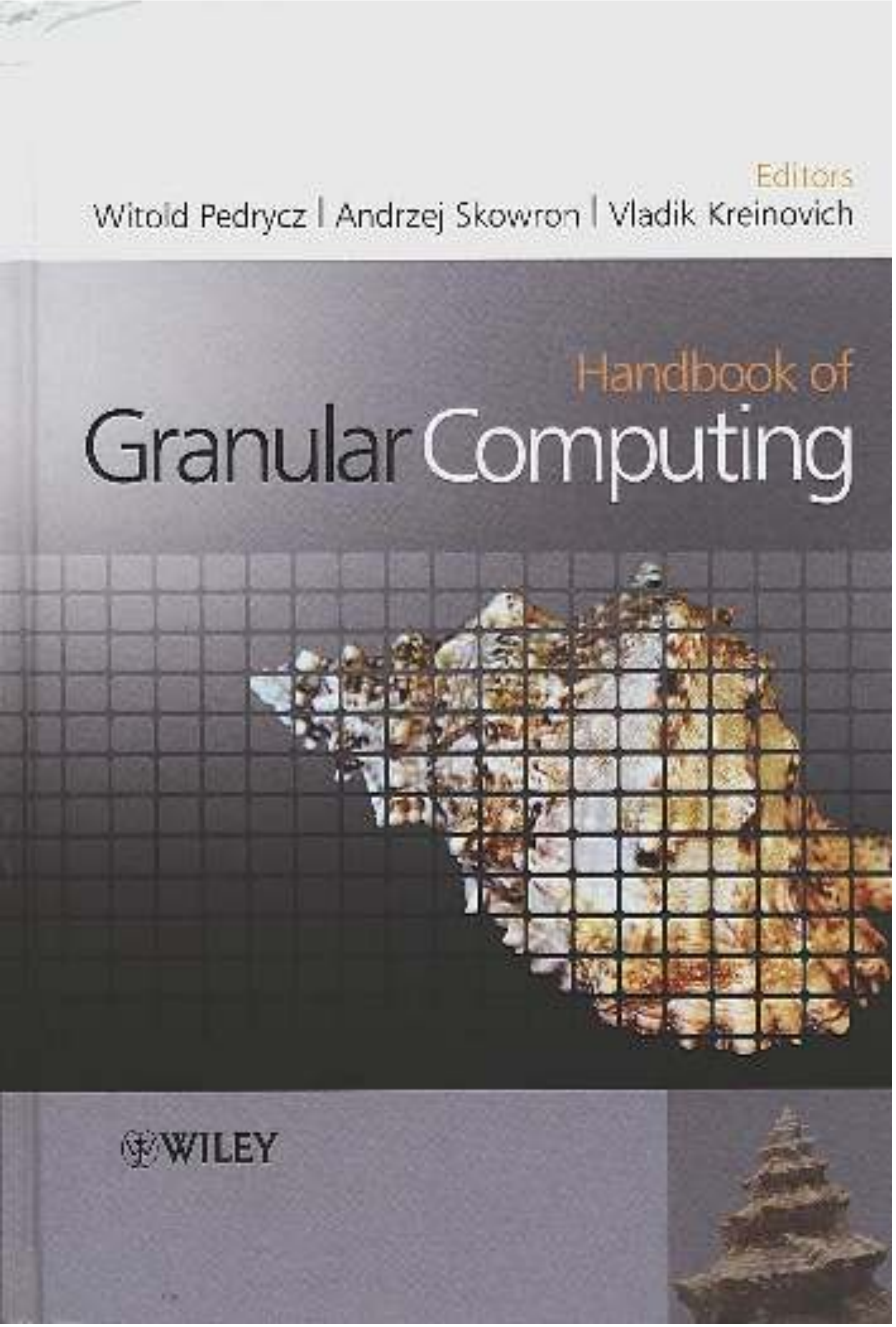


Information granulation plays a key role in implementation of the strategy of divide-and-conquer in human problem-solving

– *Lotfi A. Zadeh*

Zadeh, L.A. (1979) Fuzzy sets and information granularity. In: Gupta, M., Ragade, R., Yager, R. (eds.), Advances in Fuzzy Set Theory and Applications, Amsterdam: North-Holland Publishing Co., 3-18

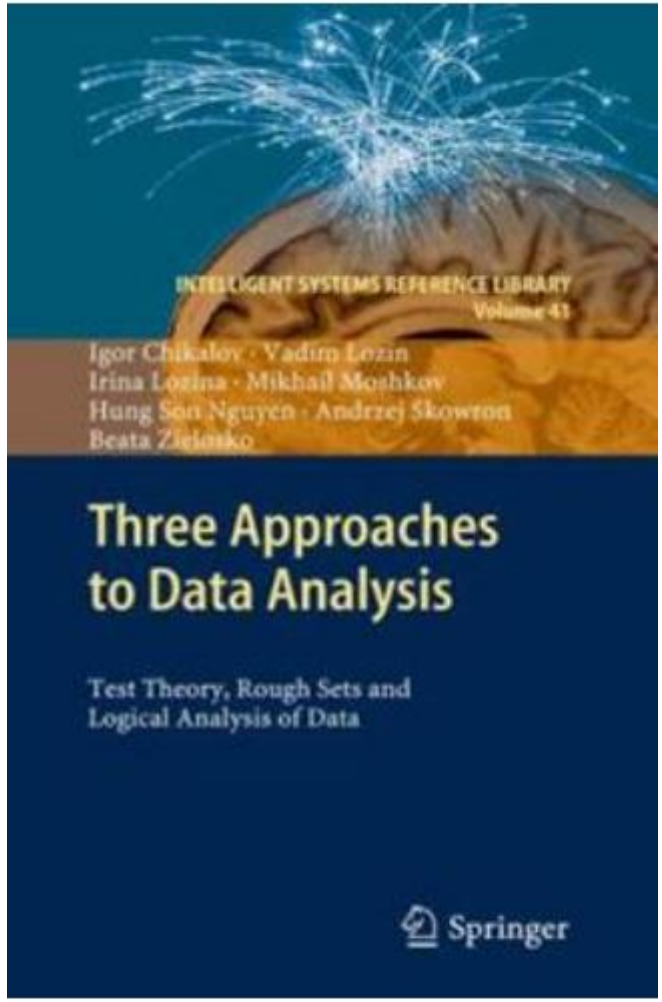
Zadeh, L.A. (2001) A new direction in AI- toward a computational theory of perceptions. AI Magazine 22(1): 73-84

ROUGH GRANULES:

ELEMENTARY GRANULES

AGGREGATION OF GRANULES: DEFINABLE GRANULES

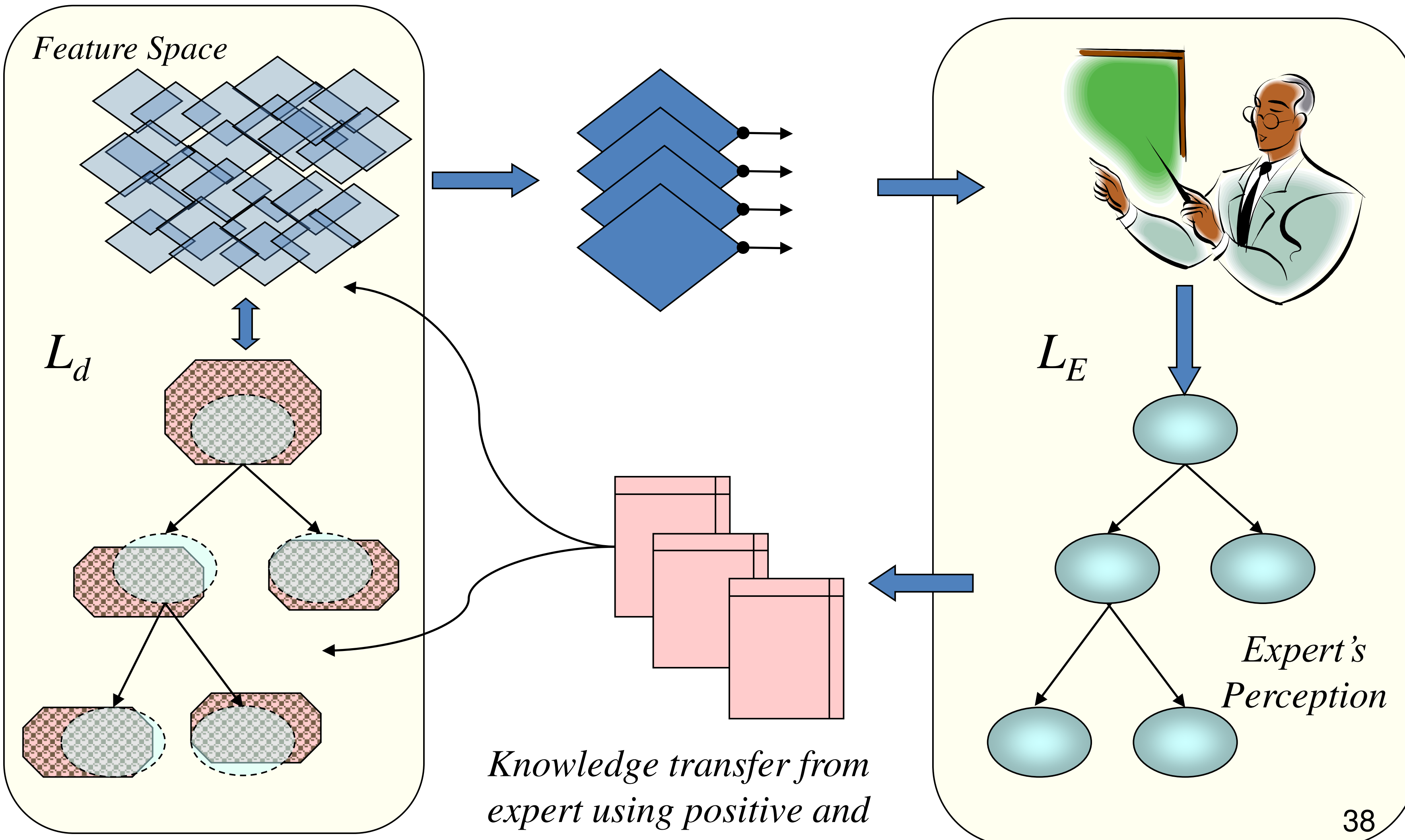
APPROXIMATION OF GRANULES (DECISION CLASSES)


INTELLIGENT SYSTEMS REFERENCE LIBRARY
Volume 41
Igor Chikalov · Vadim Lozin
Irina Lozina · Mikhail Moshkov
Hung Son Nguyen · Andrzej Skowron
Beata Zielosko
Three Approaches to Data Analysis
Test Theory, Rough Sets and Logical Analysis of Data
Springer

APPLICATIONS OF RS IN MANY AREAS

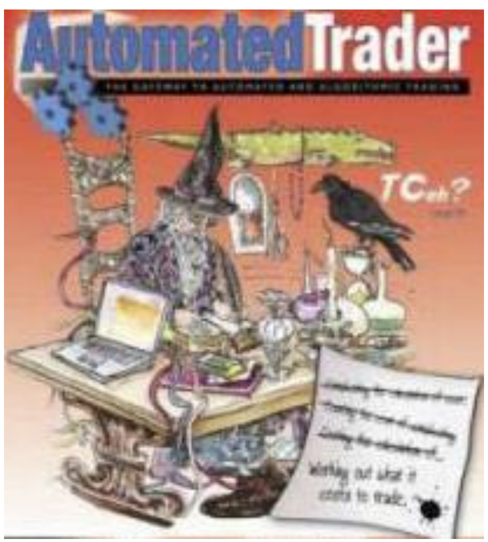
http://rsds.ur.edu.pl

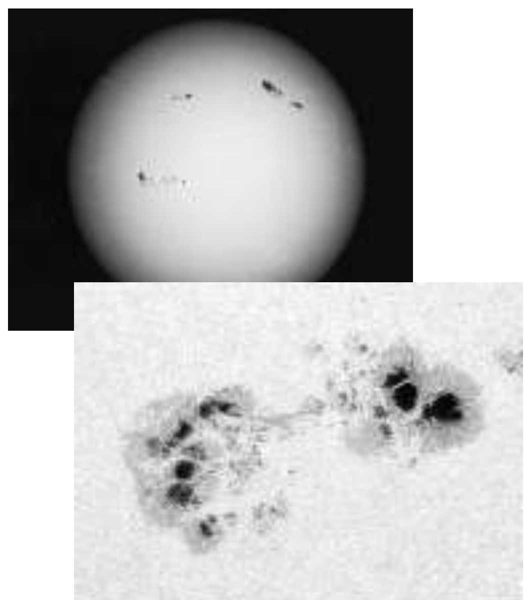
ROUGH SET BASED ONTOLOGY APPROXIMATION



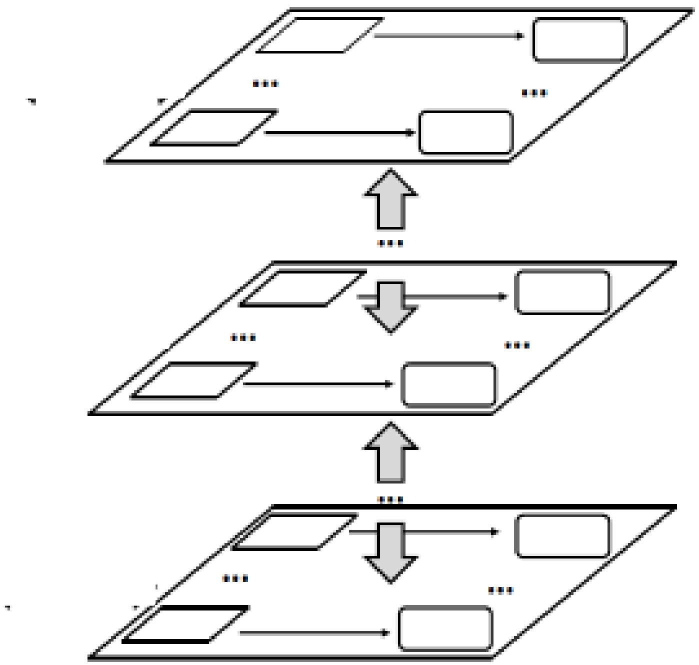
Knowledge transfer from expert using positive and negative examples

APPLICATIONS :
APROXIMATION OF COMPLEX VAGUE CONCEPTS





HIERARCHICAL GRANULES IN ABSTRACT MATHEMATICAL SPACES



i: $\mathcal{M}_i,\ L_i,\ \Vdash_i$

GRANULES: $(\alpha\,, \|\alpha\,\|),\ \propto \in L_i$

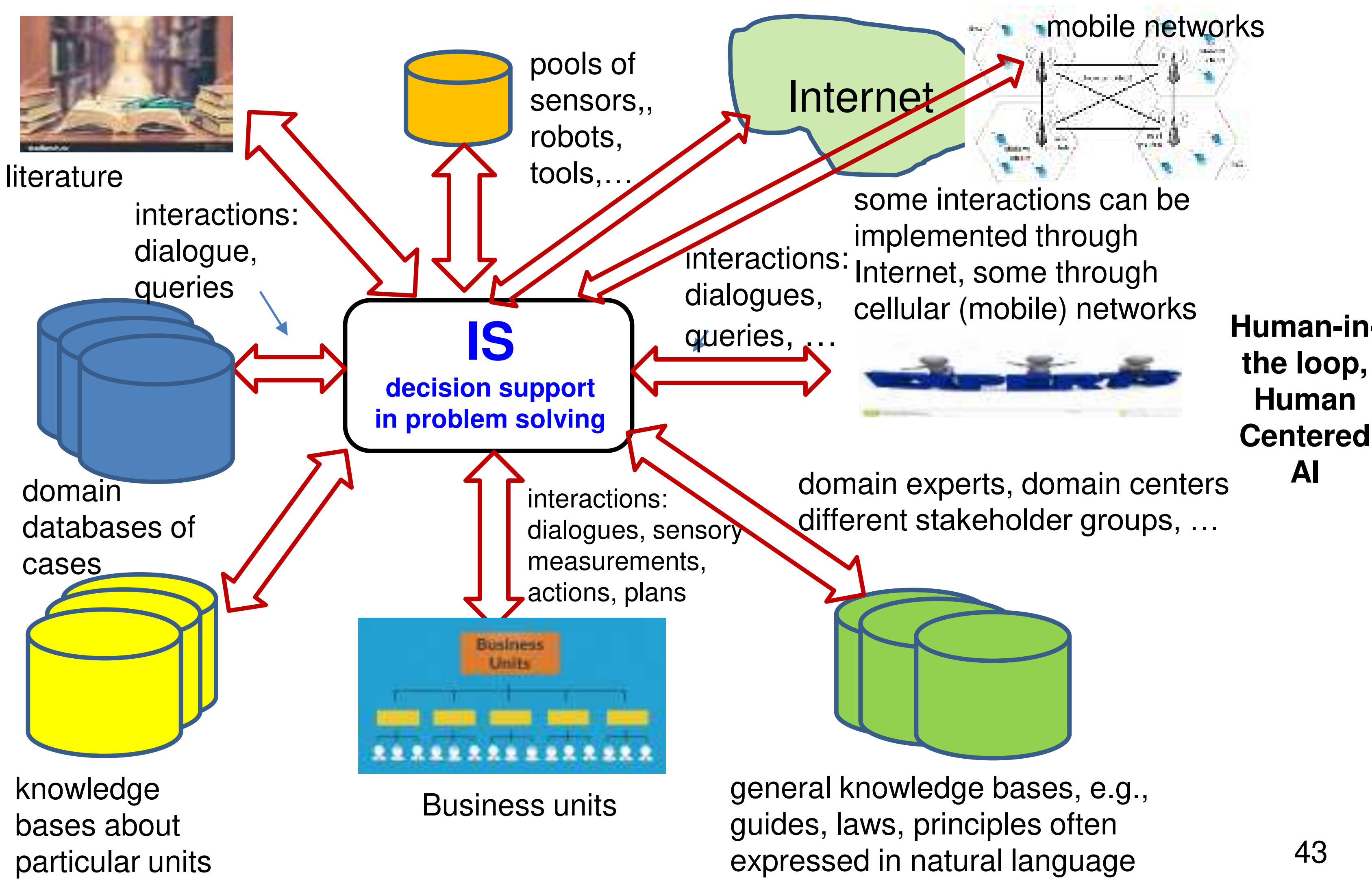
$$\|\alpha\,\| = \{M \in \mathcal{M}_i : M\ \Vdash_i \alpha\},\ \propto \in L_i$$

WHAT NEXT?

DO WE HAVE THE RELEVANT COMPUTING MODEL SUPPORTING

CYBER PHYSICAL SYSTEMS
INTERNET OF THINGS
WISDOM WEB
SOCIETY 5.0
MODELLING COMPLEX ADAPTIVE SYSTEMS
NATURAL COMPUTING
MULTISCALE MODELING
SELF-ORGANIZATION
...

IS's IN COMPLEX CONTEXT
OF INTERACTING ABSTRACT AND PHYSICAL OBJECTS



THE RELEVANT COMPUTING MODEL: FOUNDATIONS FOR DESIGN AND ANALYSIS OF IS's

Many partial proposals in many different domains exist,
e.g., multi-agent systems, machine learning, robotics, cognitive science, neuroscience, computational intelligence, natural computing, …
but we need
the relevant computing model foundations for IS's.

WE PROPOSE IGrC AS SUCH A MODEL

COMPLEX SYSTEMS

Complex system: the elements are difficult to separate. This difficulty arises from the interactions between elements. Without interactions, elements can be separated. But when interactions are relevant, elements co-determine their future states. Thus, the future state of an element cannot be determined in isolation, as it co-depends on the states of other elements, precisely of those interacting with it.

Gershenson, C., Heylighen, F.: How can we think the complex? In: Richardson, K. (Ed.): Managing Organizational Complexity: Philosophy, Theory and Application, pp. 47–61. Information Age Publishing (2005)

DEALING WITH COMPLEX PHENOMENA

Mathematics and the physical sciences made great strides for three centuries by constructing simplified models of complex phenomena, deriving, properties from the models, and verifying those properties experimentally.

This worked because the complexities ignored in the models were not the essential properties of the phenomena. **It does not work when the complexities are the essence**.

Frederick Brooks: The Mythical Man-Month: Essays on Software Engineering. Addison-Wesley, Boston, 1975. (extended Anniversary Edition in 1995).

BEYOND THE TURING TEST
&
REASONING

The Turing test, as originally conceived, focused on language and reasoning; **problems of perception and action were conspicuously absent**. The proposed tests will provide an opportunity to bring four important areas of AI research (language, reasoning, perception, and action) back into sync after each has regrettably diverged into a fairly independent area of research.

C. L. Ortitz Jr. Why we need a physically embodied Turing test and what it might look like. AI Magazine 37 (2016) 55–62.

PERCEPTUAL GRANULES: COMPLEX GRANULES (C-GRANULES)

Leslie Valiant, of Harvard University, has been named the winner of the 2010 Turing Award for his efforts to develop computational learning theory.
http://www.techeye.net/software/leslie-valiant-gets-turing-award#ixzz1HVBeZWQL

Current research of Professor Valiant
http://people.seas.harvard.edu/~valiant/researchinterests.htm

A fundamental question for artificial intelligence is to characterize the computational building blocks that are necessary for cognition.

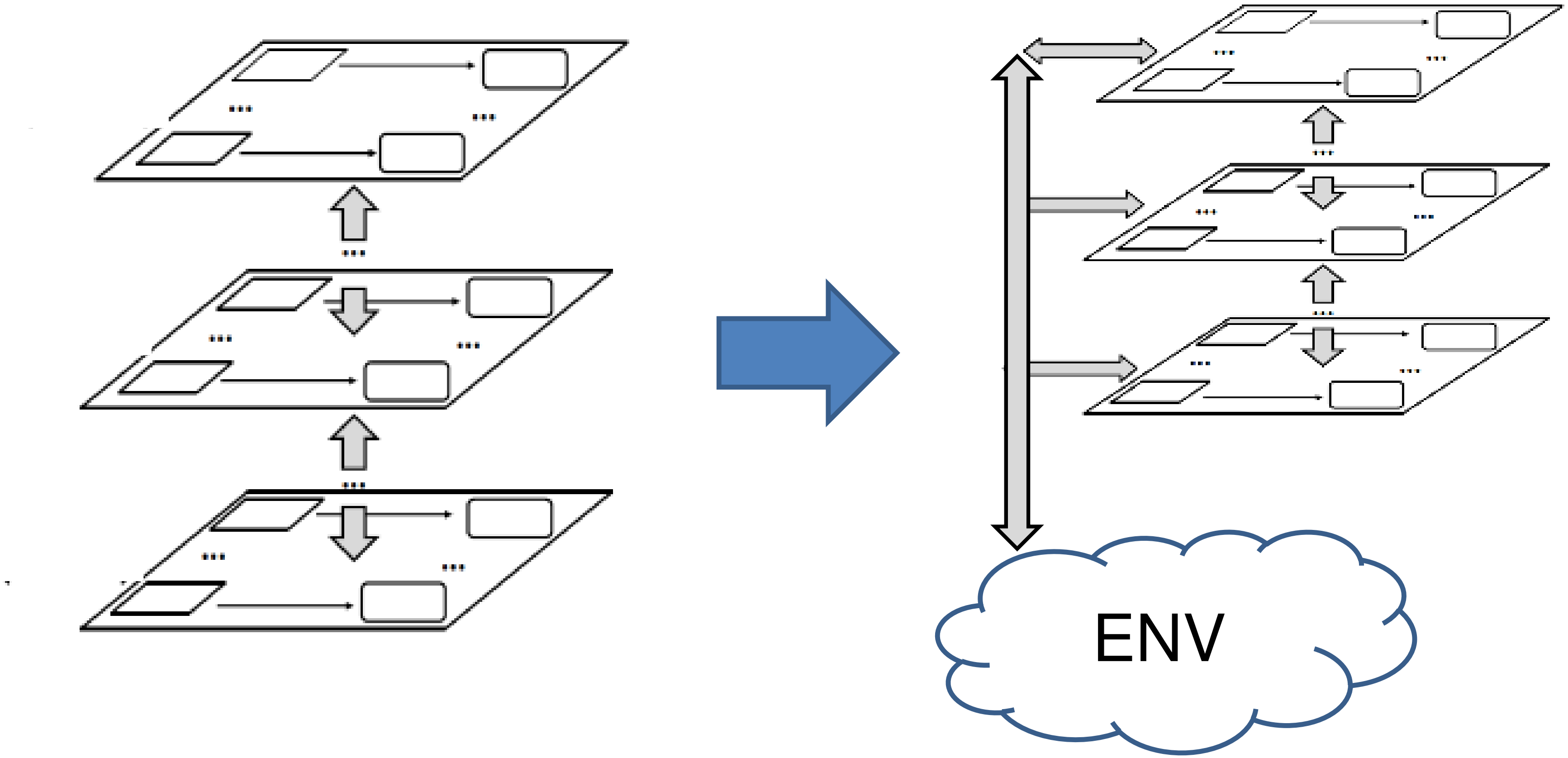
COMPLEX GRANULES

PHYSICAL SEMANTICS

Constructing the **physical part of the theory** and unifying it
with the mathematical part should be considered as one of
the main goals of statistical learning theory

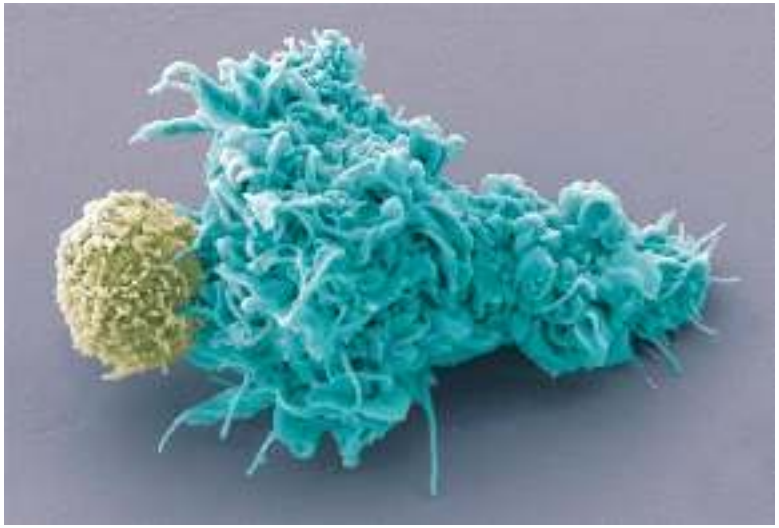
Vladimir Vapnik, Statistical Learning theory, Wiley 1998, (Epilogue: Inference from sparse data, p. 721)

PHYSICAL SEMANTICS



IMPORTANCE OF INTERACTIONS

[…] One of the fascinating goals of natural computing is to understand, in terms of information processing, the functioning of a living cell. An important step in this direction is understanding of **interactions** between biochemical reactions. … the functioning of a living cell is determined by **interactions** of a huge number of biochemical reactions that take place in living cells.



A human dendritic cell (blue pseudo-color) in close interaction with a lymphocyte (yellow pseudo-color). This contact may lead to the creation of an immunological synapse.

The Immune Synapse by Olivier Schwartz and the Electron Microscopy Core Facility, Institut Pasteur

http://www.cell.com/Cell_Picture_Show

Andrzej Ehrenfeucht, Grzegorz Rozenberg: Reaction Systems: A Model of Computation Inspired by Biochemistry, LNCS 6224, 1–3, 2010

INTERACTIVE GRANULAR COMPUTING (IGrC)

=

GrC +

INTERACTIONS OF PHYSICAL OBJECTS +

PERCEPTION+

REASONING (JUDGMENT)

POSTULATES

Physical objects exist in the physical space and are embedded into its parts.

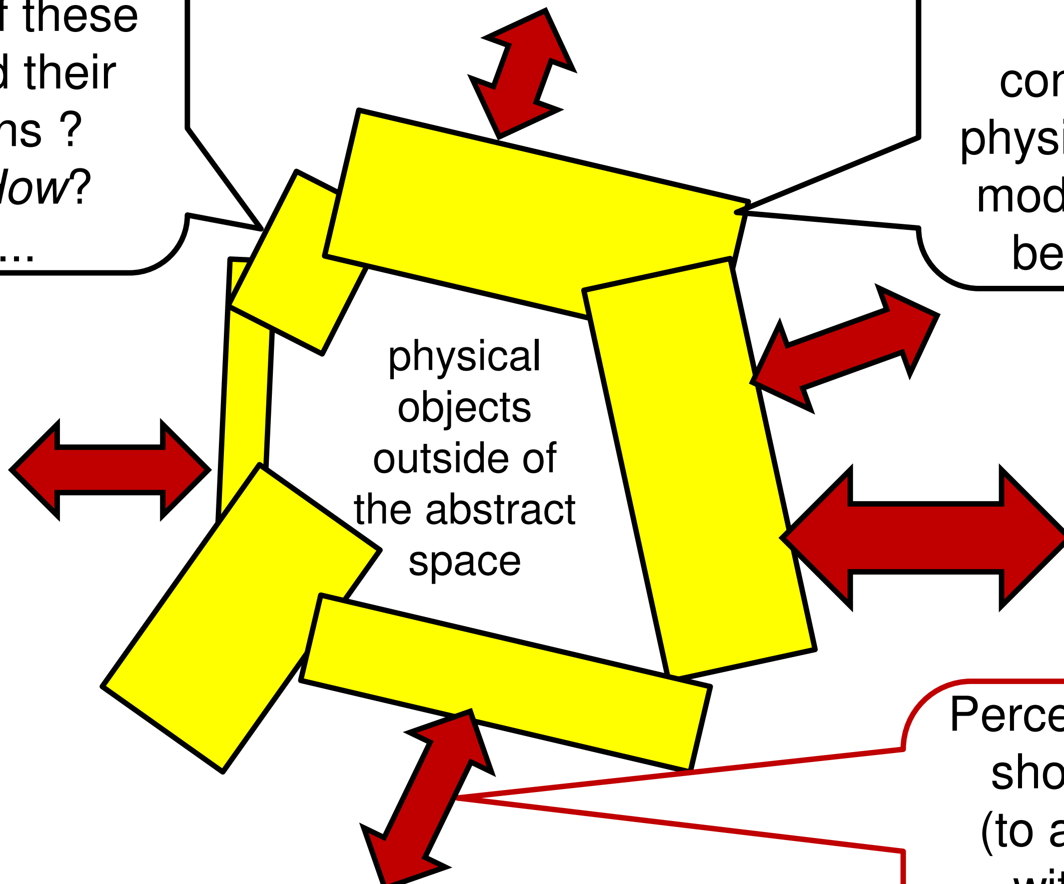
Physical objects are interacting in the physical space, and thus some collections of physical objects may create dynamical systems in the physical space.

Some properties of physical objects or their configurations as well as their interactions can be perceived by c-granules.

PROBLEMS

How to perceive properties of these objects and their interactions ? *Where*? *How*? *When*?...

How to generate the relevant configurations of physical objects and modify interactions between them?



Perceived properties should be robust (to a high degree) with respect to unpredictable interactions from the environment

NICHES

J.Holland: Signals and Boundaries.
Building Blocks for Complex Adaptive Systems, MIT 2012

A niche is a diverse array of agents that regularly exchange resources and depend on that exchange for continued existence. […] The niche, then, is made up of physical and virtual boundaries that determine the limits of [these] interactions.
[...]. The invisible boundaries that define niches are a complex topic, still only partly understood.

COMPLEX GRANULES (C-GRANULES)

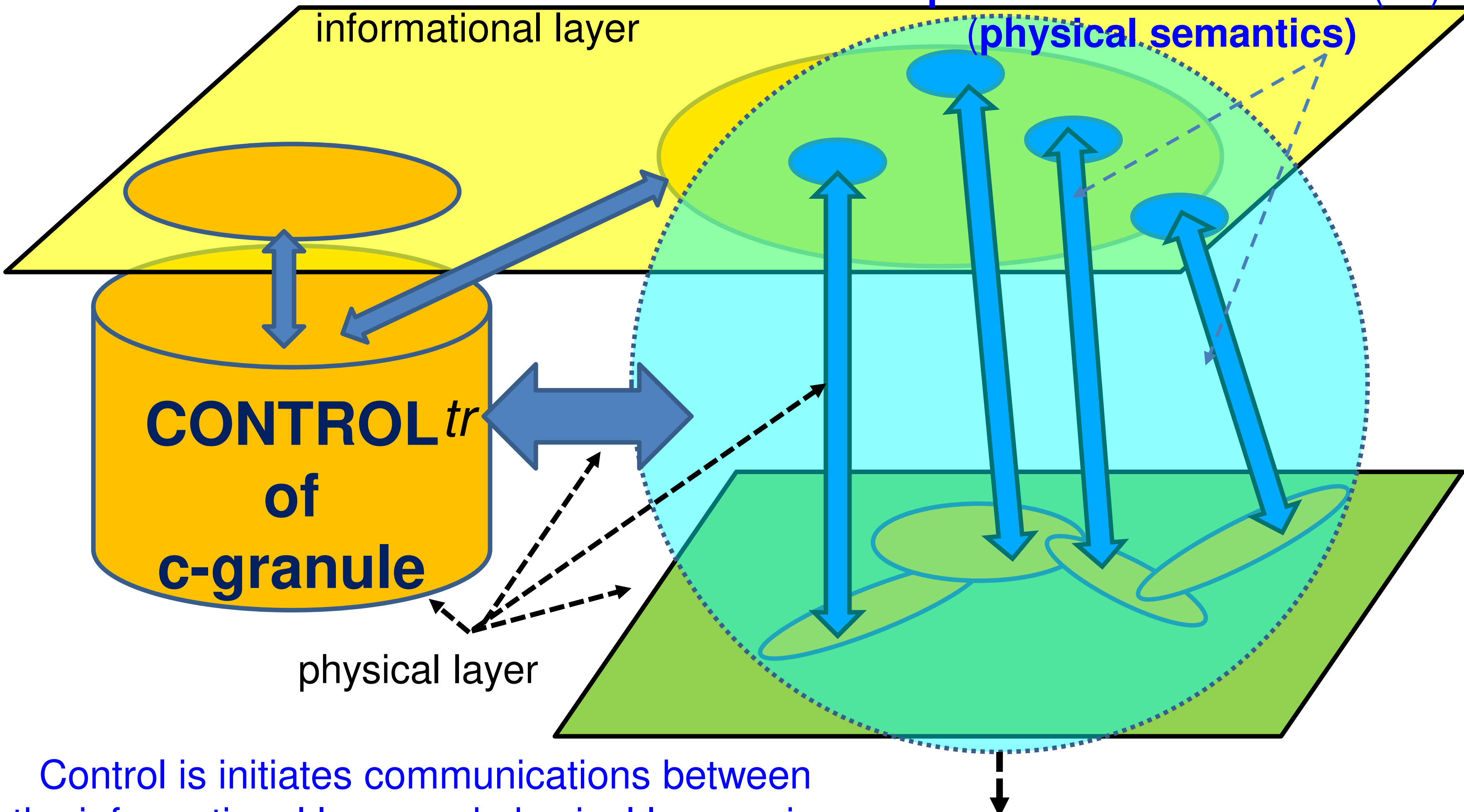
Informational-physical complex granules (ipc-granules or *c-granules*, for short) -- linking abstract and physical spaces

Special cases:

- *information gran*ules in the abstract space -- granules considered in GrC
- *physical granules* (*p*-granules, for short) -- granules in the physical space
- *network of c-granules*

C-GRANULE: INTUITION

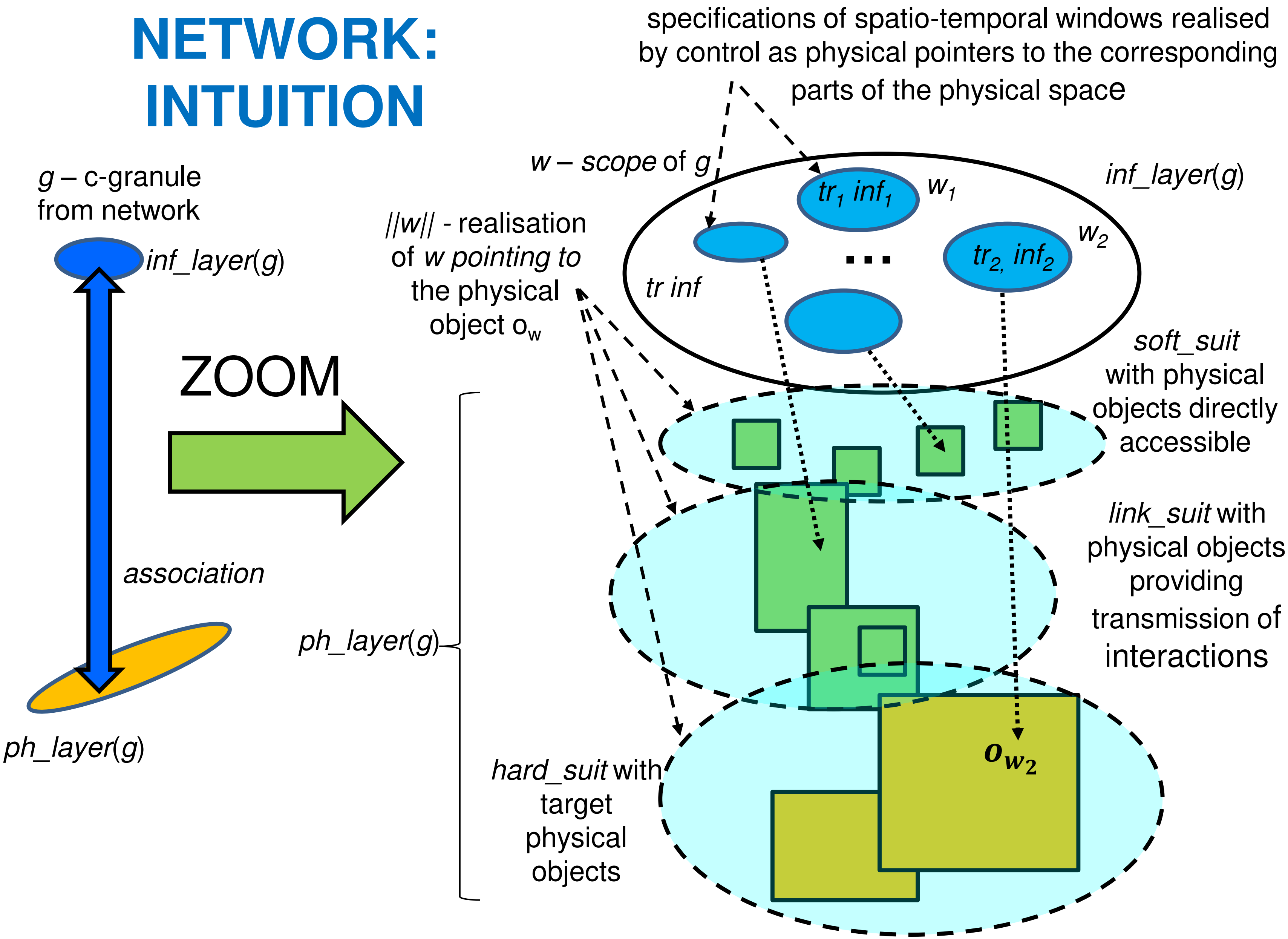
Associations between informational and physical layers realized by **implementational module** (**IM**) (**physical semantics**)



Control is initiates communications between the informational layer and physical layer using relevant ic-granules (generated by its IM)) allowing to collect in the informational layers properties of perceived physical objects and their interactions.

NETWORK OF INFORMATIONAL COMPLEX GRANULES DEALING WITH ABSTRACT AND PHYSICAL OBJECTS

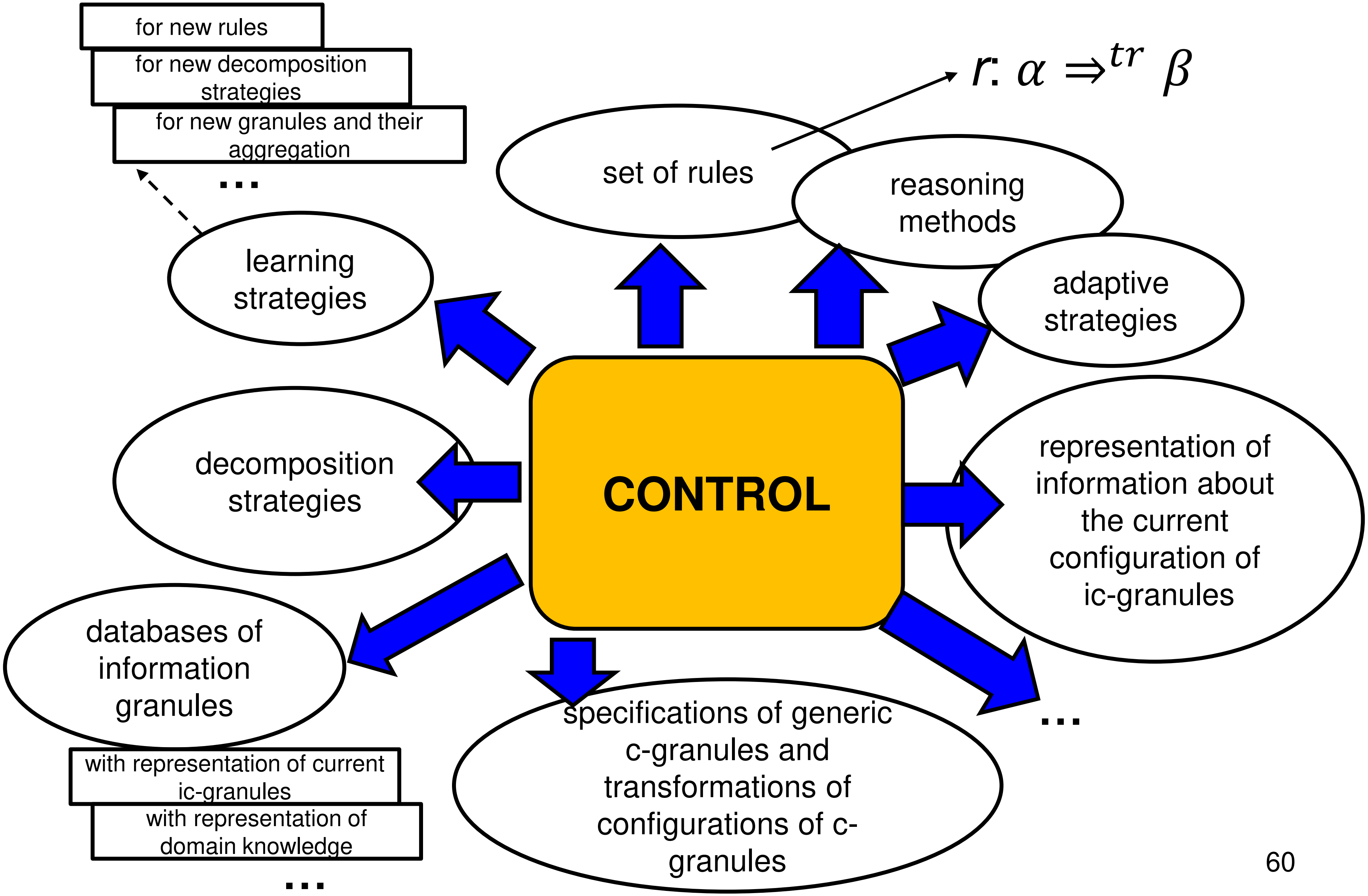
C-GRANULE FROM NETWORK: INTUITION



BASIC CONTROL MODULES

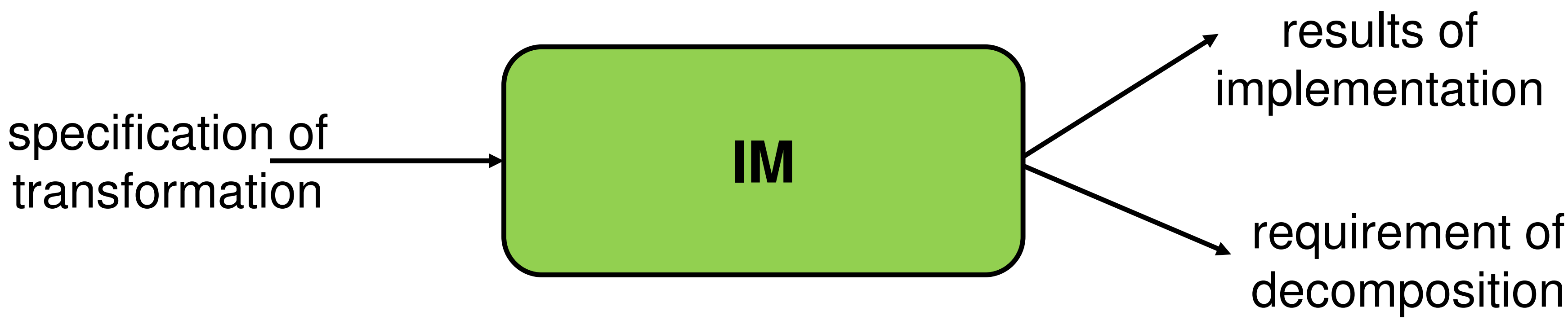
- RULE MODULE
- IMPLEMENTATIONAL MODULE
- DECOMPOSITION MODULE
- REASONING MODULE

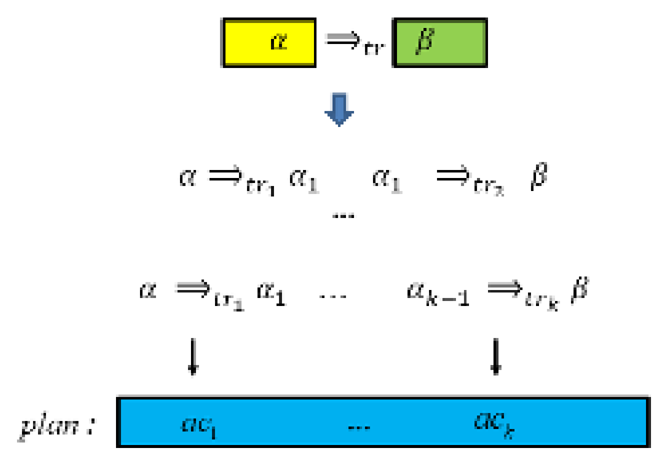
CONTROL: INTUITION



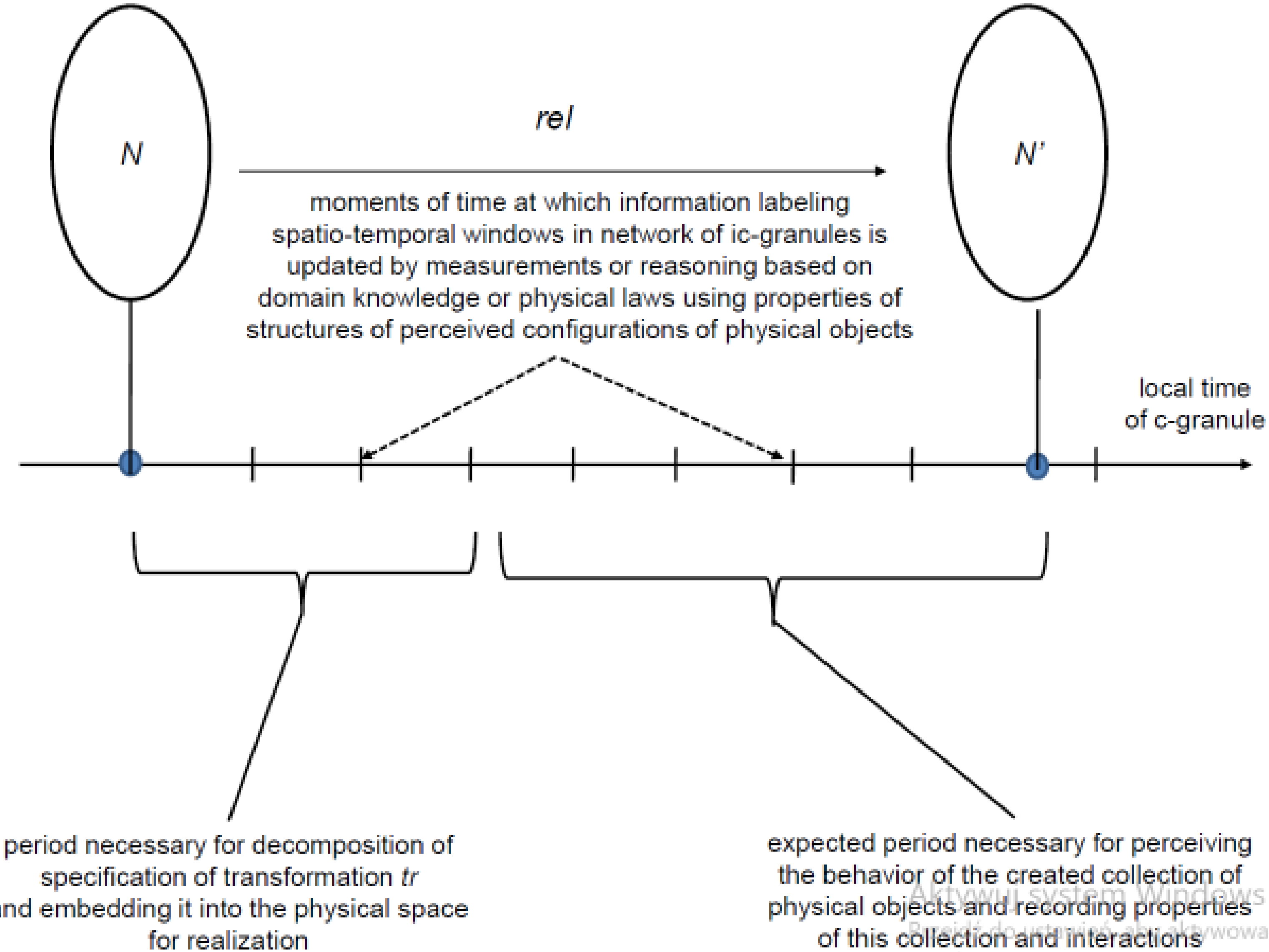
IMPLEMANTATIONAL MODULE (IM)

IM plays a crucial role in interaction of abstract and physical objects; IM realizes physical semantics





RULE MODULE & TRANSITON RELATION ON NETWORKS OF C-GRANULES



REASONING MODULE

LESLIE VALIANT: TURING AWARD 2010

.

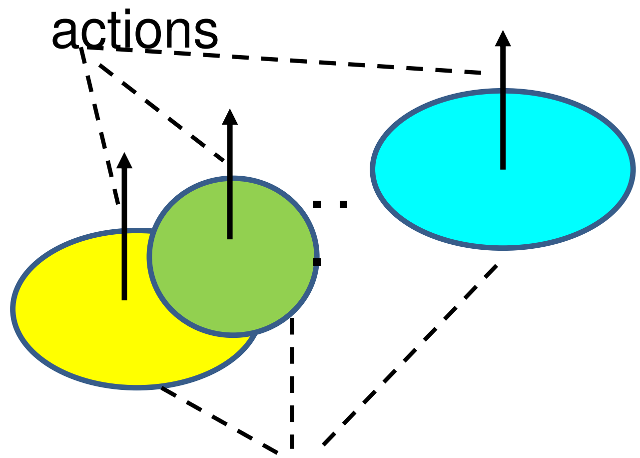
A specific challenge is to build on the success of machine learning so as to cover broader issues in intelligence.

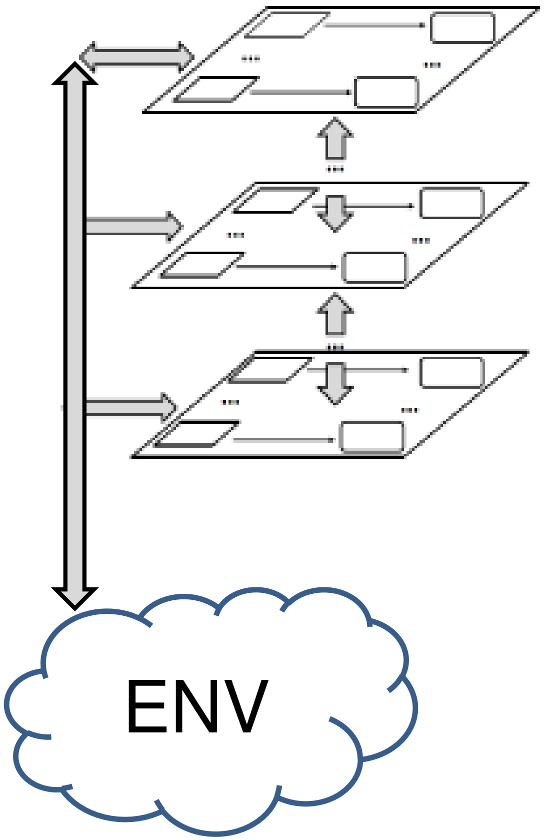
This requires, in particular a reconciliation between two contradictory characteristics - the apparent logical nature of reasoning and the statistical nature of learning.

Professor Valiant has developed a formal system, called robust logics, that aims to achieve such a reconciliation.

REASONING (JUDGMENT) REALIZED OVER INTERACTIVE COMPUTATIONS COMPOSED OUT OF NETWORKS OF C-GRANULES SUPPORTING REALIZATION OF PERCEPTION

i.e. understanding the perceived situation to satisfactory degree for making the right decisions





where, what, how, when,…

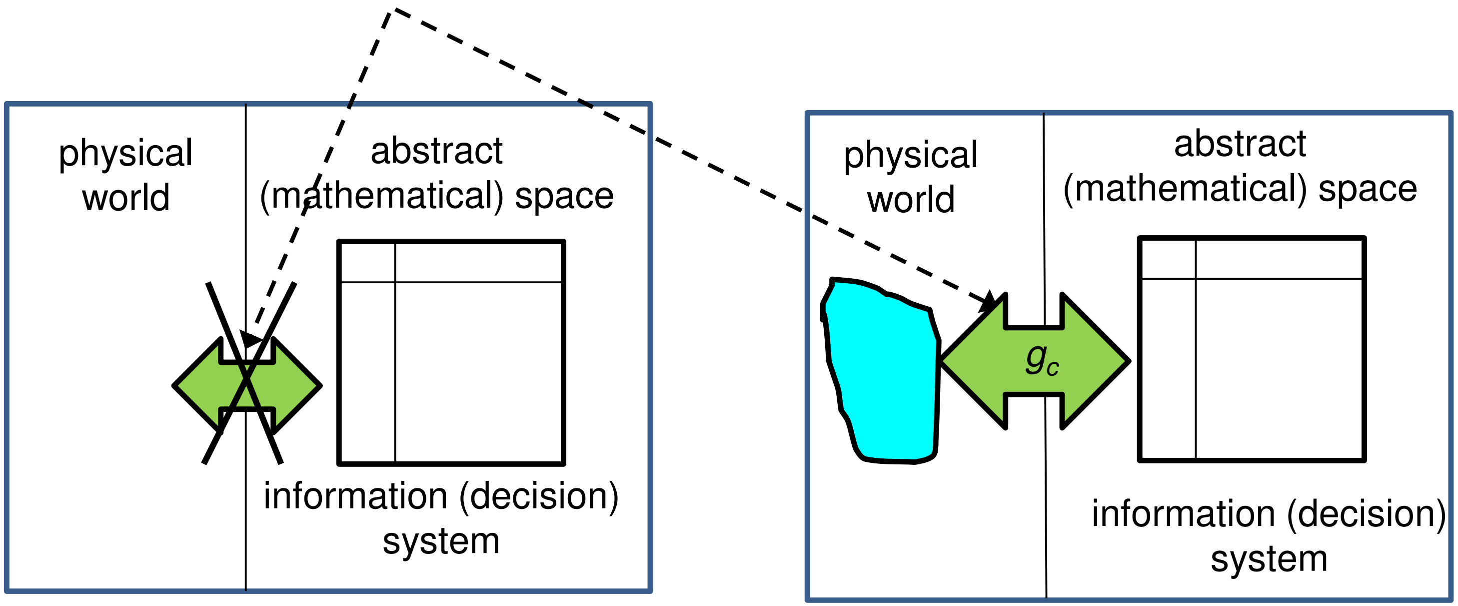
JUDGMENT SUPPORTING
-- IN CONTINUOUS INTERACTION
WITH THE PHYSICAL WORLD --
DISCOVERY OF
RELEVANT STRUCTURES
AND
COMPUTATIONAL BUILDING
BLOCKS (GRANULES) OVER THEM
FOR COGNITION

PERCEPTUAL APPROACH TO RS: APPROXIMATION OF CONCEPTS BASED ON REASONING (JUDGMENT)

RS: PERCEPTUAL APPROACH

Information(decision) systems are parts of dynamic objects: c-granules

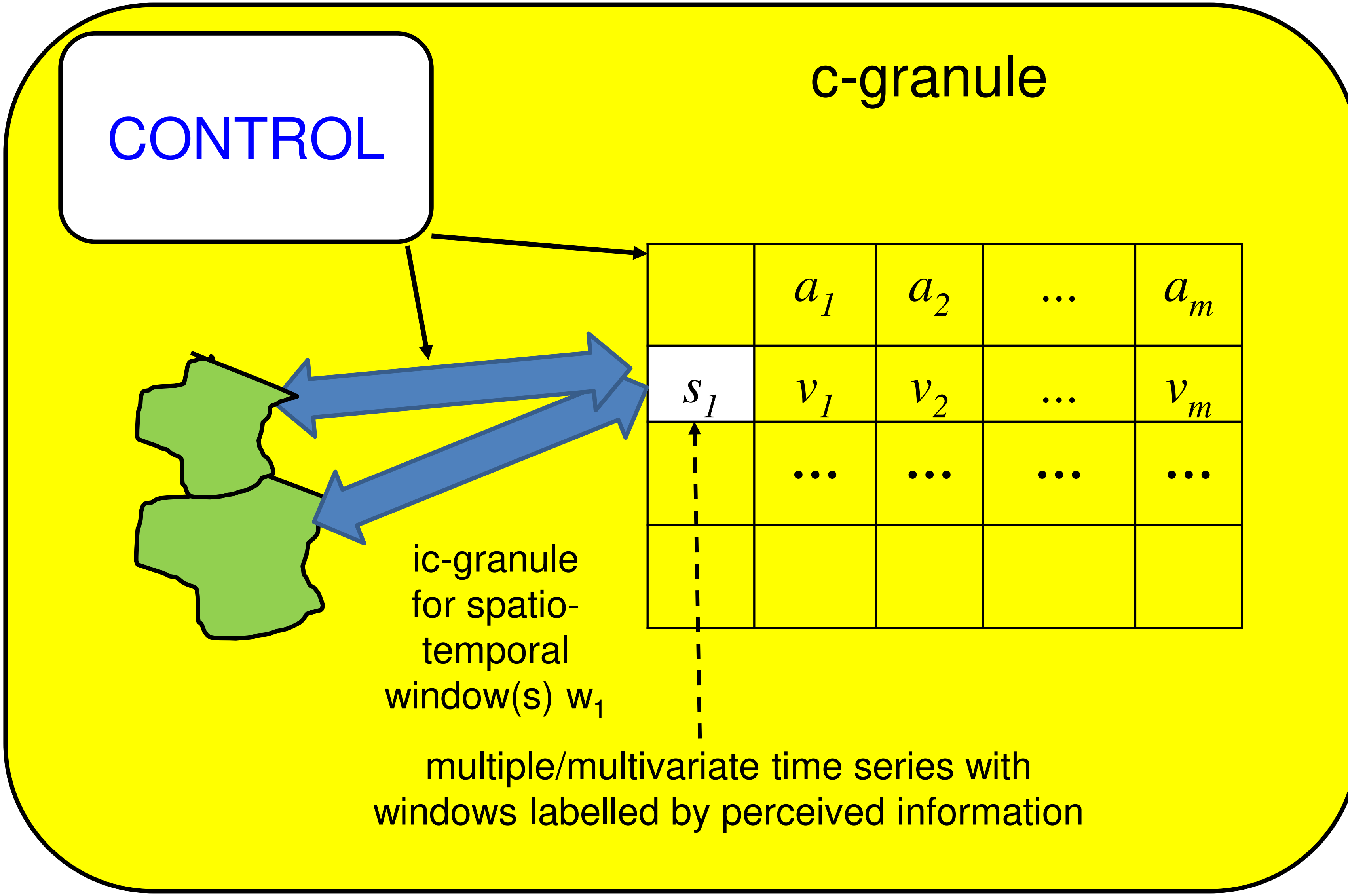
Continuous interactions with the physical world during perceiving of the current situation aiming to understand this situation to a degree satisfactory for making the rights decisions



In the existing approaches to rough sets interactions with the physical world are omitted.
Information systems are **GIVEN** as pure mathematical objects.

Rough sets in IGrC (perceptual approach) based on **physical semantics**:: information (decision) systems are obtained as the result of granulation of information perceived by c-granule g_c in the physical world.

UNCERTAINTY IN OBJECT PERCEPTION INDISCERNIBILITY RELATIONS



ADAPTIVE RS:
RULES FOR CHANGING COMPLEX GAMES

Control of c-granule is aiming to provide the most relevant decision systems for approximation of concepts.

Information (decision) systems

- are represented in informational layer of c-granule; they are not isolated, *given* objects
- have a dynamic structure modified by control of c-granule and (indirectly by) interactions with the environment;

Objects: (fragments of) multiple and/or myltivariate time series represented in informational layer of c-granule as the result of perceiving the situation in the physical world along computations of c-granule over networks of c-granules

Attributes: properties of such objects; necessity of providing possibility to change the currently used attributes during computation in identification of situation (making it possible to select the relevant transformations for realization)

Decisions: elements of complex game – pairs (complex vague concept, labeled by specification of transformation (e.g. decision (plan)) related to this concept)

Complex games are discovered from such decision tables; approximation of different complex vague concepts is necessary.

ADAPTIVE RS:
RULES FOR CHANGING COMPLEX GAMES

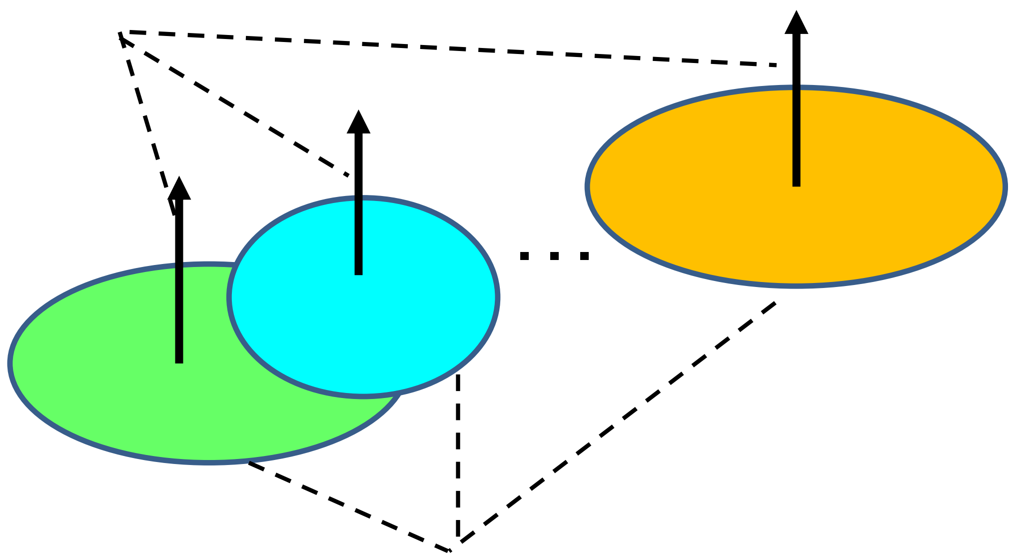
Necessary reasoning (judgment) methods supporting:

- discovery of complex games and their adaptation (reasoning about changes – rough calculus)
- identification of the relevant properties of situations in the physical world
- control of computations over networks of c-granules toward generating computations satisfying a given specification; this may be related to the whole computation or to its final state
  - in the case of fuzzy sets: membership degrees of the perceived in the physical world situations to the considered concepts;
  - in the case of rough sets membership degrees to approximation regions of the considered concepts
- resolving conflicts between rules specifying transformation to be performed
- discovery of new sources of the relevant for the considered problem data (data governance)
- discovery of compound sensors and/or actuators, robots

…

ADAPTIVE RS:
RULES FOR CHANGING COMPLEX GAMES

complex games for situations with the relevant properties



complex vague concepts
triggering complex games

DYNAMIC SPACE OF REASONING CONSTRUCTIONS (NOT PURELY MATHEMATICAL!) AS THE BASIS FOR CONCEPT (CLASSIFICATION) APPROXIMATION

IGrC creates the basis for dynamically changing reasoning constructions, used for approximation of concepts (classifications) in Interactive Intelligent Systems. **The required reasoning methods are far more rich than nowadays used in constructing the rough set-based approximations of concepts**.

REASONING (JUDGMENT) ABOUT CONSTRUCTION OF APPROXIMATION REGIONS AND MEMBERSHIP TO THEM IS PERFORMED ALONG COMPUTATIONS OVER NETWORKS OF C-GRANULES

IGrC BASED FOUNDATIONS FOR IS's

RS & FS IN IS's

CONTROL

RISK MANAGEMENT

DATA SCIENCE

COLLECTIVE INTELLIGENCE

INTELLIGENCE UNDERSTANDING

...

NATURE OF JUDGMENT

Reliability of inductive reasoning based on statistical learning theory based on VC-dim.

Harman, S. Kulkarni: Reliable Reasoning: Induction and Statistical Learning Theory. The MIT Press, 2007.

- DEDUCTION
- INDUCTION
- ABDUCTION
- ...

figures in:
explanation of behavior,
inference,
experience.

Hence the theory of judgment has a place in: psychology, logic, phenomenology.

Wayne M. Martin: Theories of Judgment. Psychology, Logic, Phenomenology. Cambridge Univ. Press (2006).

EXAMPLES OF WHITE SPOTS OR PARTIALLY RECOGNIZED AREAS ON THE MAP OF REASONING (JUDGMENT)

EXAMPLES OF WHITE SPOTS

Reasoning supporting

- perception of situations in the physical world
- learning ecorithms
- complex games and their adaptation
- searching for relevant data e.g. data governances
- generation of robust networks of c-granules
- practical, experience based reasoning: dialogues with humans
- decomposition: CWW
- conflict resolution
- extracting the relevant knowledge from domain data bases
- societies of c-granules satisfying given requirements

HOW TO DISCOVER THE RELEVANT LANGUAGE FOR REASONING?

Language discovery: Natural computing is the field of research that investigates models and computational techniques inspired by nature and, dually, **attempts to understand the world around us in terms of information processing**.

Lila Kari, Grzegorz Rozenberg: The many facets of natural computing. Commun. ACM 51(10): 72-83 (2008)

Explainability in natural language: Whenever I saw another breakthrough in artificial intelligence or machine learning hit the press, I came back to the same question: How does it work? The curious thing to me was that I'd spent countless hours studying and practicing machine learning in academia and industry, and yet I still couldn't consistently answer that question.

Sean Gerrish: How smart machines think. MIT Press 2019

SUMMARY

We discussed some aspects of

- evolution of RS models;
- IGrC model as the base for design IS’s dealing with complex phenomena;
- perceptual approach to RS in IS’s based on IGrC having potential to handle the grounding problem by bridging a connection between the abstract mathematical modeling and the real physical semantics.

FOUNDATIONS BASED ON IGrC FOR IS's DEALING WITH COMPLEX PHENOMENA

Tomorrow, I believe, we will use
IS's
to support our decisions
in defining our research strategy and specific aims,
in managing our experiments,
in collecting our results, interpreting our data,
in incorporating the findings of others,
in disseminating our observations,
in extending (generalizing) our experimental observations
- through exploratory discovery and modeling -
in directions completely unanticipated

Bower, J.M., Bolouri, H. (Eds.): Computational Modeling of Genetic and Biochemical Networks. MIT Press, Cambridge, MA (2001)

Z. Pawlak: Rough sets. International Journal of Computer and Information Sciences 11 (1982)
Z. Pawlak: Rough sets. Theoretical Aspects of Reasoning About Data. Kluwer (1991)
Z. Pawlak, A. Skowron:
Rudiments of rough sets. Inf. Sci. 177(1) 3-27 (2007)
Rough Sets: Some Extensions. Inf. Sci. 177(1) 28-40 (2007)
Rough Sets and Boolean Reasoning. Inf. Sci. 177(1) 41-73 (2007)
A. Skowron, Z. Suraj (eds.): Rough Sets and Intelligent Systems. Professor Zdzisław Pawlak in Memoriam. Series Intelligent Systems Reference Library 42-43, Springer, Heidelberg (2013)
J. Kacprzyk, W. Pedrycz (eds.), Handbook of Computational Intelligence, Springer (2015) (part on rough sets).
G. Wang, A. Skowron, Y. Yao, D. Ślęzak, L. Polkowski (eds.): Thriving Rough Sets: 10th Anniversary - Honoring Professor Zdzisław Pawlak's Life and Legacy & 35 years of Rough Sets. Studies in Computational Intelligence 708, Springer, Heidelberg (2017)
A. Skowron, D. Ślęzak: Rough Sets Turn 40: From Information Systems to Intelligent Systems. FedCSIS 2022 Proceedings, pp. 23–34.
Rough Set Database System (RSDS) http://rsds.ur.edu.pl

IGrC publications, e.g.: https://dblp.uni-trier.de/pers/hd/s/Skowron:Andrzej
A. Skowron, D. Ślęzak: Rough Sets in Interactive Granular Computing: Toward Foundations for Intelligent Systems Interacting with Human Experts and Complex Phenomena. IJCRS 2023.

THANK YOU!