ROUGH SETS
IN
INTERACTIVE GRANULAR COMPUTING:
TOWARD
FOUNDATIONS FOR INTELLIGENT SYSTEMS INTERACTING
WITH COMPLEX PHENOMENA AND HUMAN EXPERTS

Andrzej Skowron
Systems Research Institute
Polish Academy of Sciences
&
QED Software

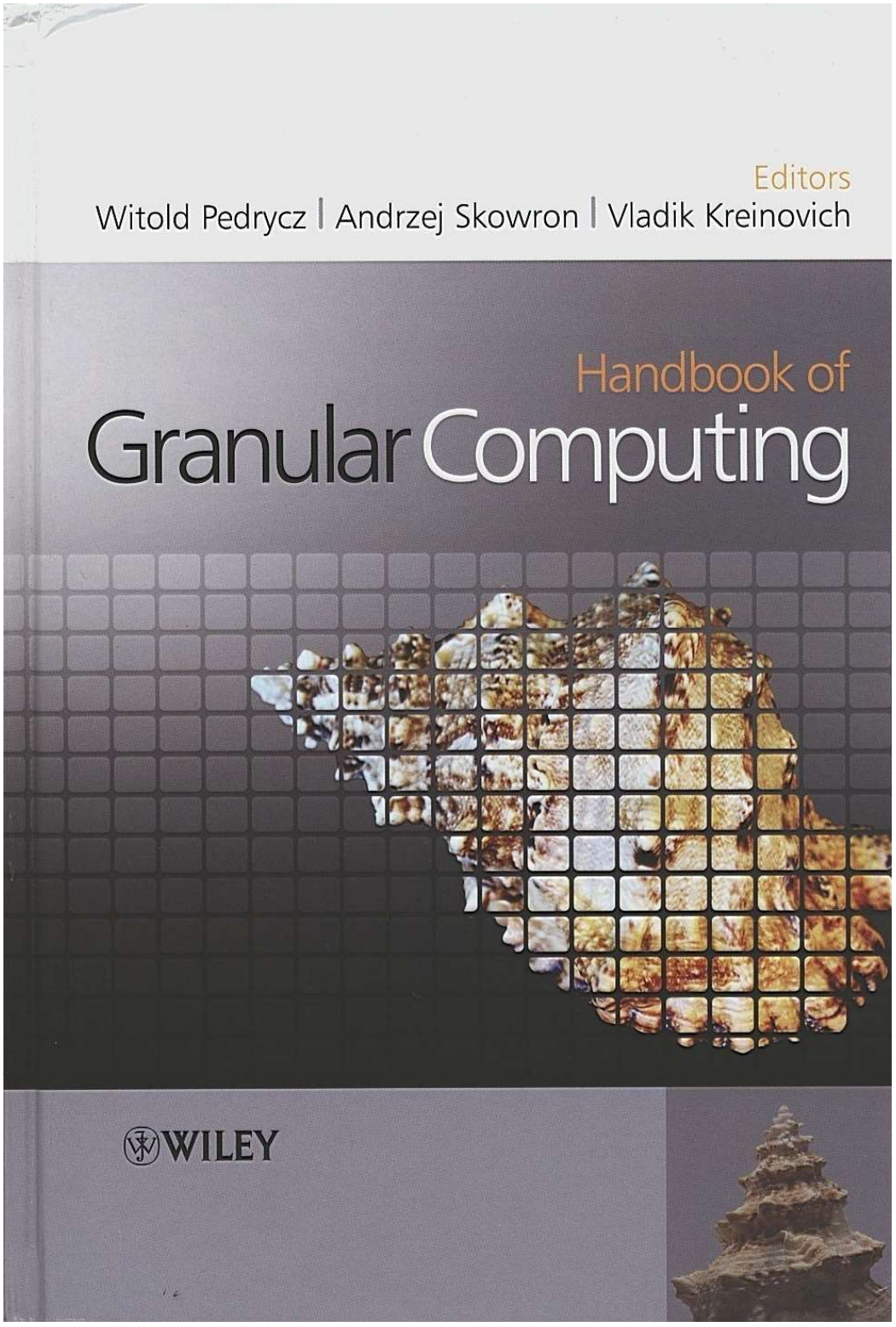
International Joint Conference on Rough Sets (IJCRS 2023), October 5-8,2023, Cracow, Poland

To
Professors
Helena Rasiowa
and
Zdzisław Pawlak
in memoriam

AGENDA

- Rough sets (RS) and granular computing (GrC)
- Motivations for development of a new computing model for Intelligent Systems (IS's) based on Interactive Granular Computing (IGrC)
- IGrC preliminaries
  - Informational-physical complex granules (icp-granules, c-granules)
    - Networks of c-granules
    - Control
- Rough sets in IGrC
- Summary

GrC & RS



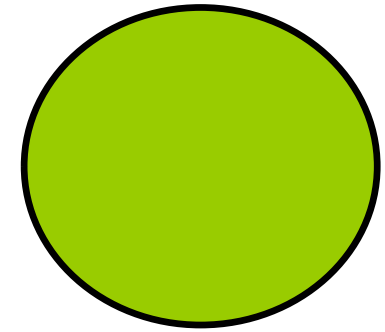
Information granulation plays a key role in implementation of the strategy of divide-and-conquer in human problem-solving

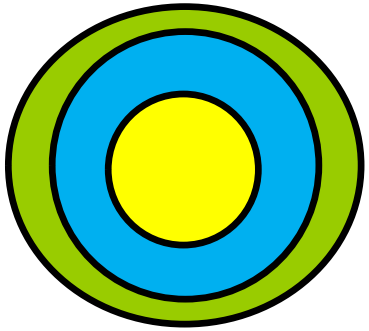
– Lotfi A. Zadeh

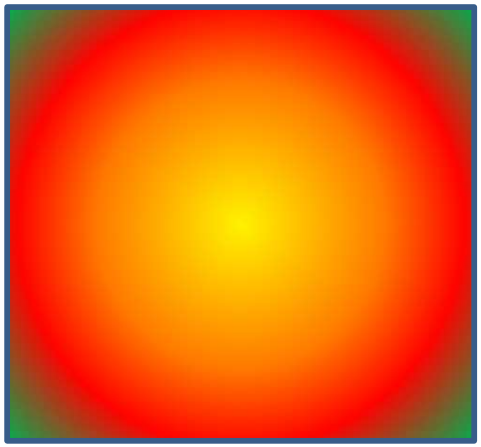
Zadeh, L.A. (1979) Fuzzy sets and information granularity. In: Gupta, M., Ragade, R., Yager, R. (eds.), Advances in Fuzzy Set Theory and Applications, Amsterdam: North-Holland Publishing Co., 3-18

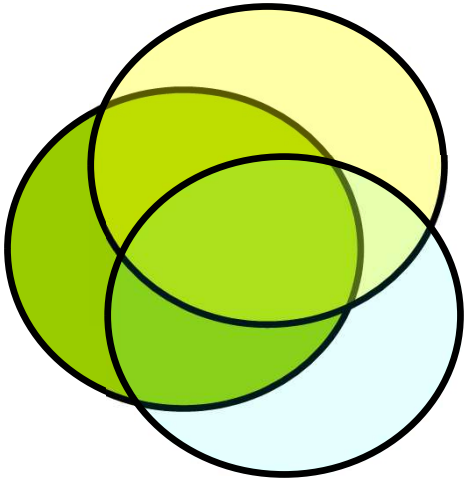
Zadeh, L.A. (2001) A new direction in AI-toward a computational theory of perceptions. AI Magazine 22(1): 73-84

ELEMENTARY GRANULES + OPERATIONS ON GRANULES = CALCULI OF GRANULES









...

ROUGH GRANULES:

ELEMENTARY GRANULES

AGGREGATION OF GRANULES, e.g., DEFINABLE GRANULES

APPROXIMATION OF GRANULES

UNCERTAINTY IN OBJECT PERCEPTION
INDISCERNIBILITY RELATIONS

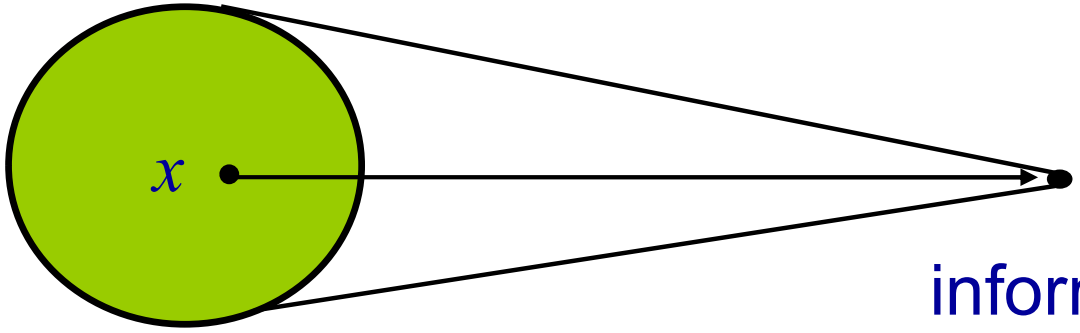
GIVEN information system (data table)

$IS = (U, A)$

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

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

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



neighborhood of x

elementary granule

$u = Inf_A(x)$

information signature of x

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

τ

tolerance or similarity

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

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

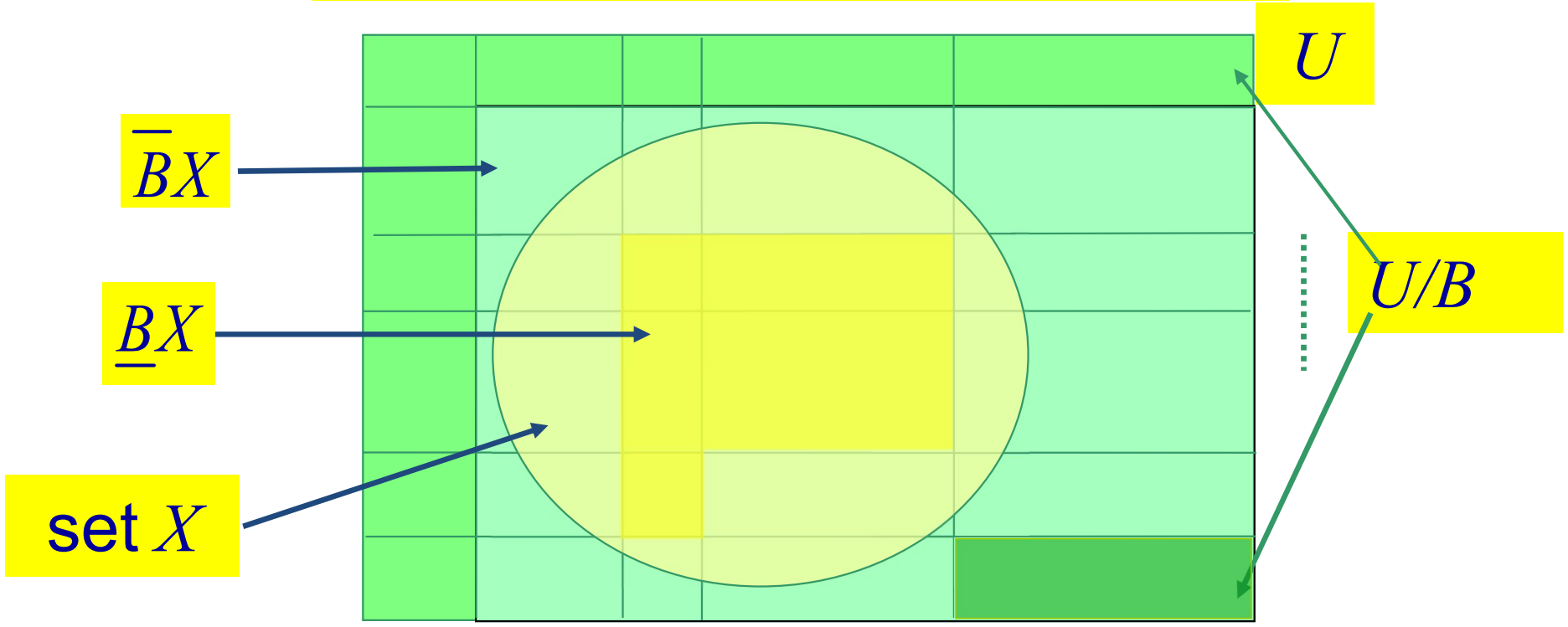
$U / B = \{[x]_B : x \in U\}$

LOWER AND UPPER APROXIMATION

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

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

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



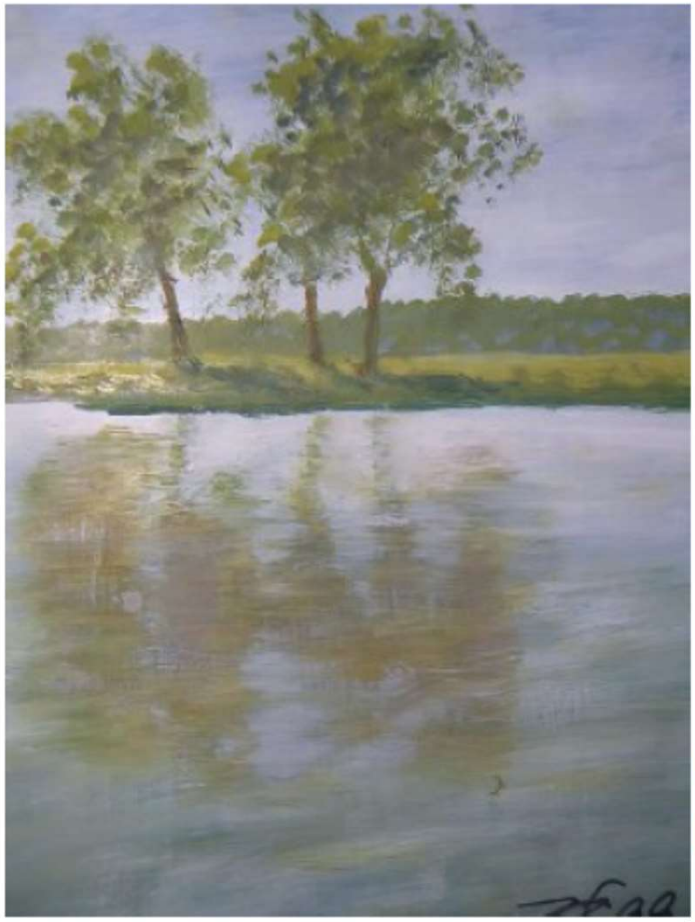
BOUNDARY REGION

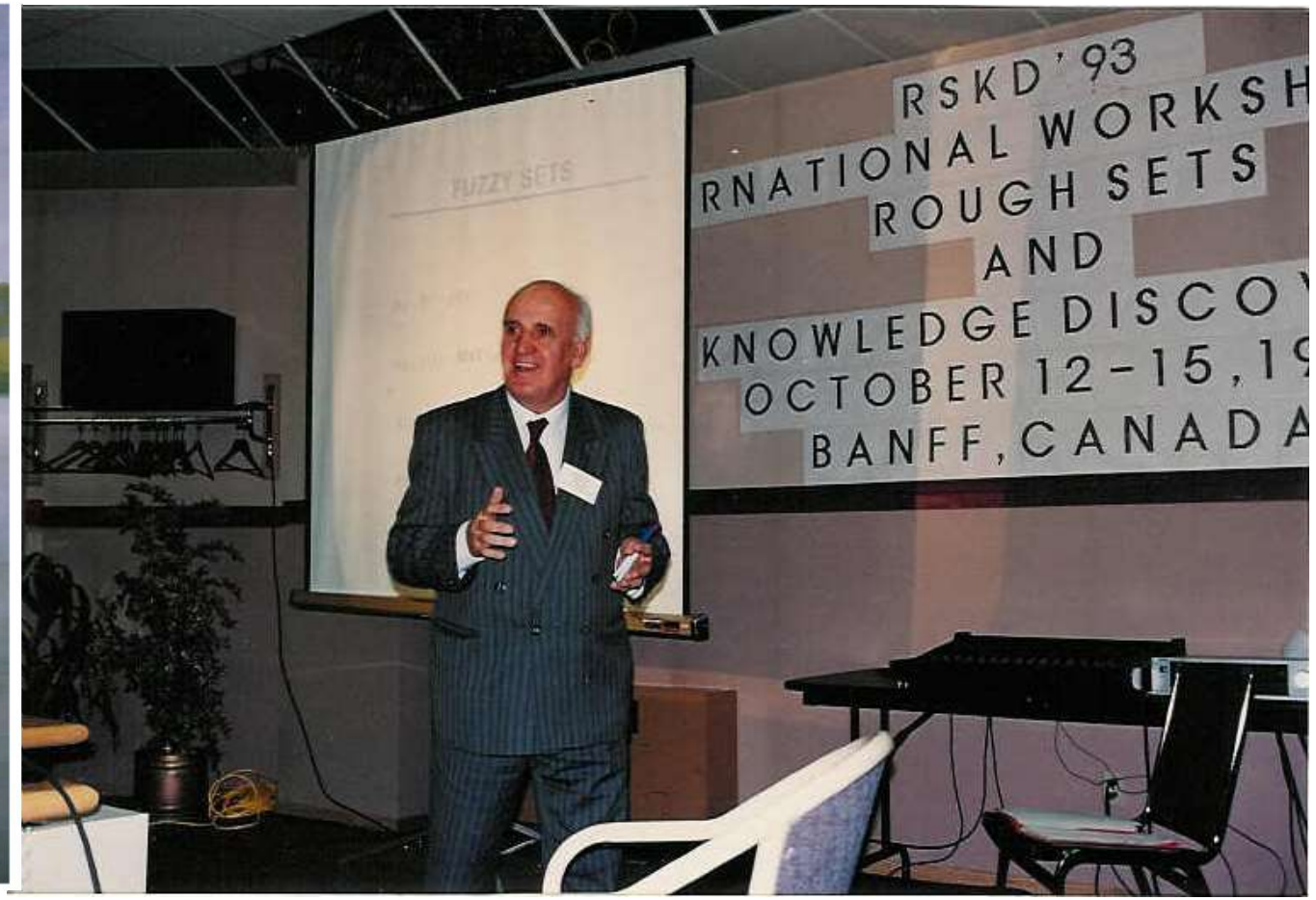
$$BN_B(X) = \overline{B}X \setminus \underline{B}X$$

ROUGH SETS

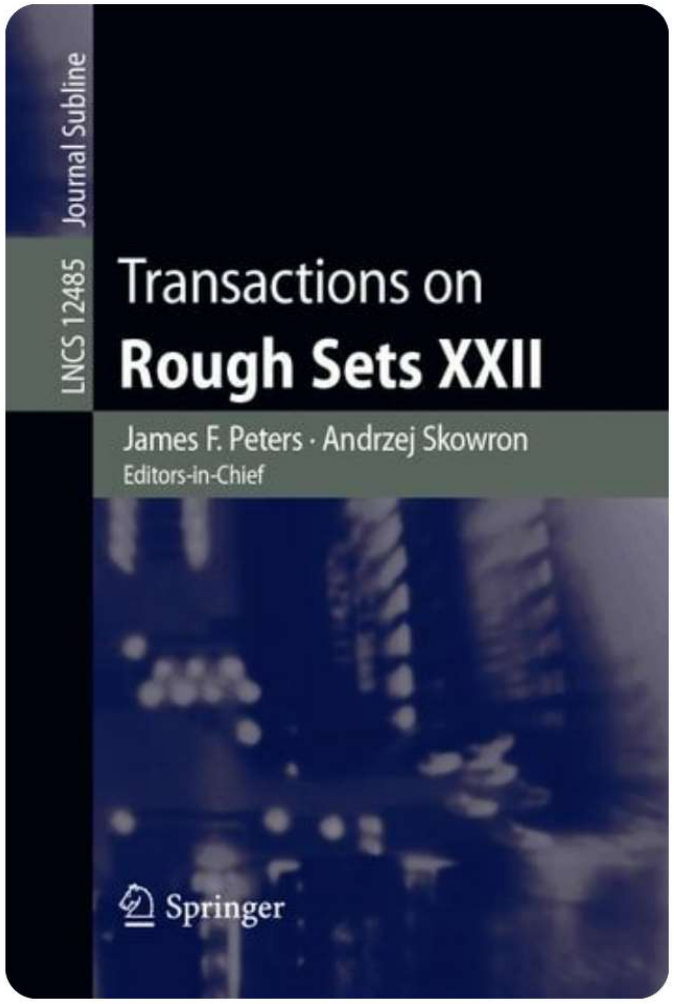
Pawlak, Z.: Rough sets. International Journal of Computer and Information Sciences 11 (1982)

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

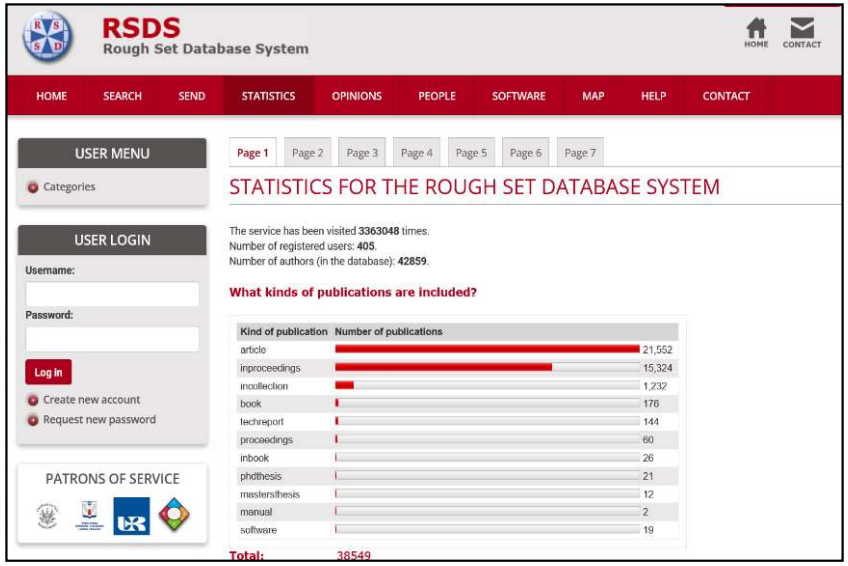




After 40 years: many thousands of papers http://rsds.ur.edu.pl



ACM Transactions on Intelligent Systems and Technology
Annals of Pure and Applied Logic
Applied Intelligence
Applied Soft Computing
Artificial Intelligence
Artificial Intelligence Review
BMC Bioinformatics
Communications of the ACM
European Journal of Operational Research
Expert Systems with Applications
Fundamenta Informaticae
Fuzzy Sets and Systems
Group Decision and Negotiation
IEEE Transactions on Computational Social Systems
IEEE Transactions on Evolutionary Computation
IEEE Transactions on Fuzzy Systems
IEEE Transactions on Geoscience and Remote Sensing
IEEE Transactions on Image Processing
IEEE Transactions on Knowledge and Data Engineering
IEEE Transactions on Neural Networks
IEEE Transactions on Systems, Man and Cybernetics
IEEE/ACM Transactions on Audio, Speech, and Language Processing
IEEE/ACM Transactions on Computational Biology and Bioinformatics
Information Sciences
International Journal of Approximate Reasoning
International Journal of Computational Intelligence Systems
International Journal of Machine Learning and Cybernetics
International Journal of Molecular Science
International Journal of Science and Engineering
Journal of Applied Non-Classical Logics
Journal of Biomedical Informatics
Knowledge and Information Systems
Knowledge Based Systems
Neural Computing and Applications
Neural Networks
Neural Processing Letters
Neurocomputing
Pattern Recognition
Pattern Recognition Letters
Pharmaceutics
Sensors
Studia Logica
Theoretical Computer Science
Web Intelligence and Agent Systems...



COMBINATIONS OF ROUGH SETS WITH OTHER APPROACHES

GENERALIZATIONS OF ROUGH SETS

RELATIONSHIPS OF RS WITH OTHER APPROACHES

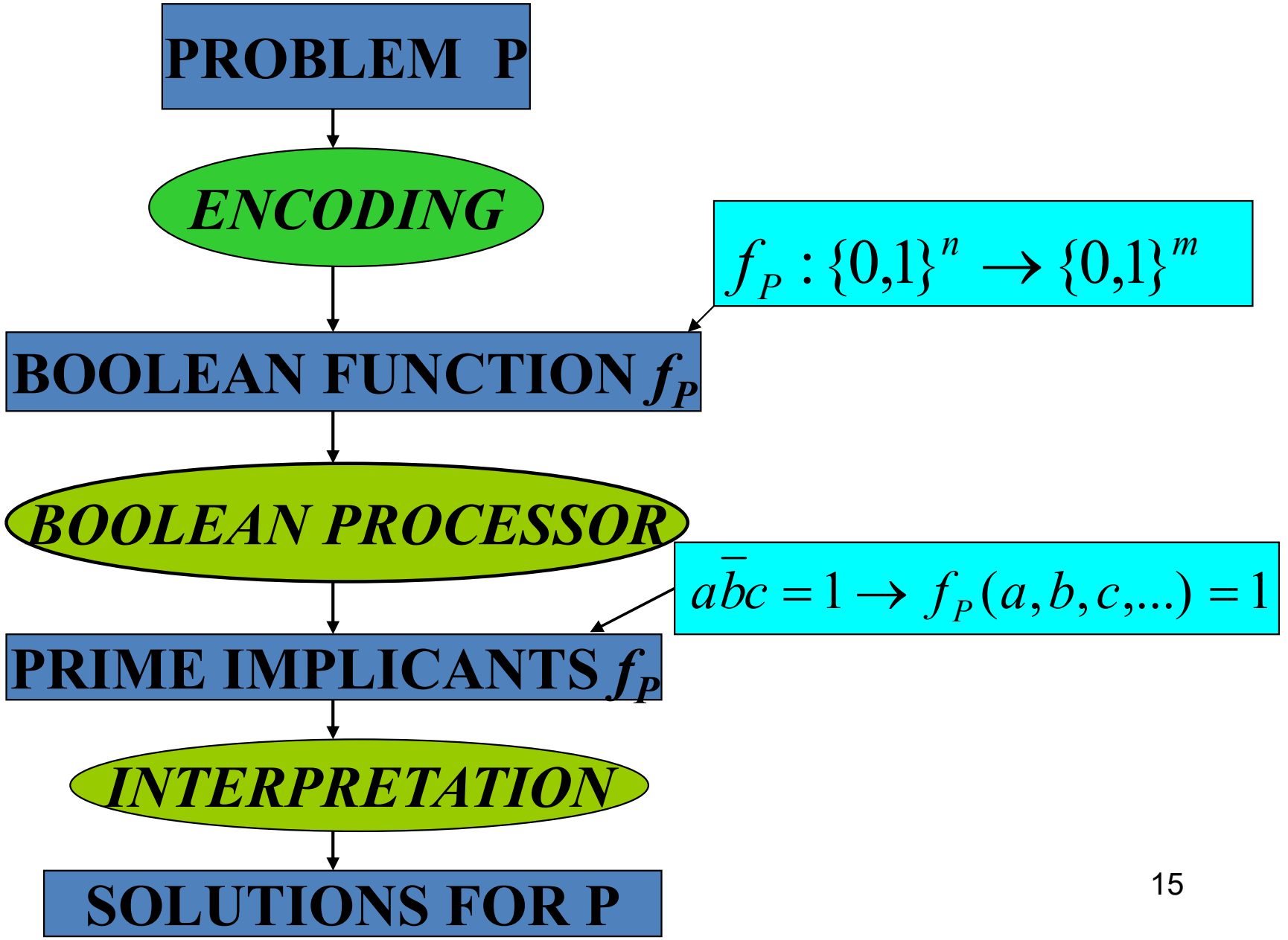
COMBINATIONS OF ROUGH SETS WITH OTHER APPROACHES

- 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
- ...

RELATIONSHIPS OF ROUGH SETS WITH BOOLEAN REASONING

BOOLEAN REASONING

George Boole (1815-1864)



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

RS & DEMPSTER-SHAFER THEORY

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

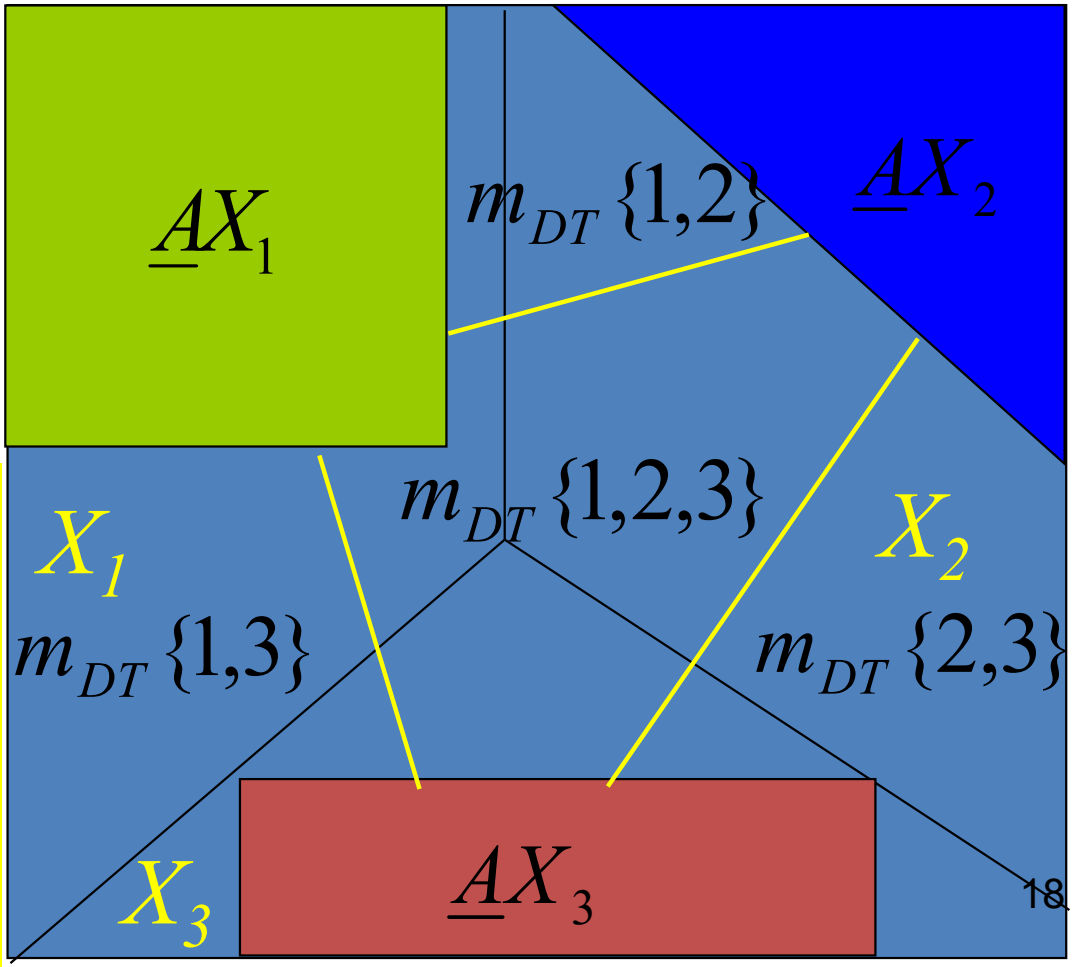
gen. decision: $\delta_A(x) = d([x]_A)$

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

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

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

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



UNCERTAINTY IN SELECTION (DISCOVERY) OF RELEVANT APPROXIMATION SPACE

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

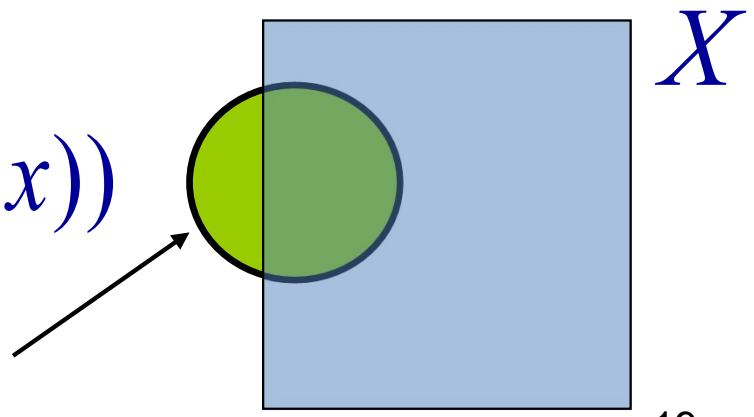
$$AS = (U, N, \nu)$$

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

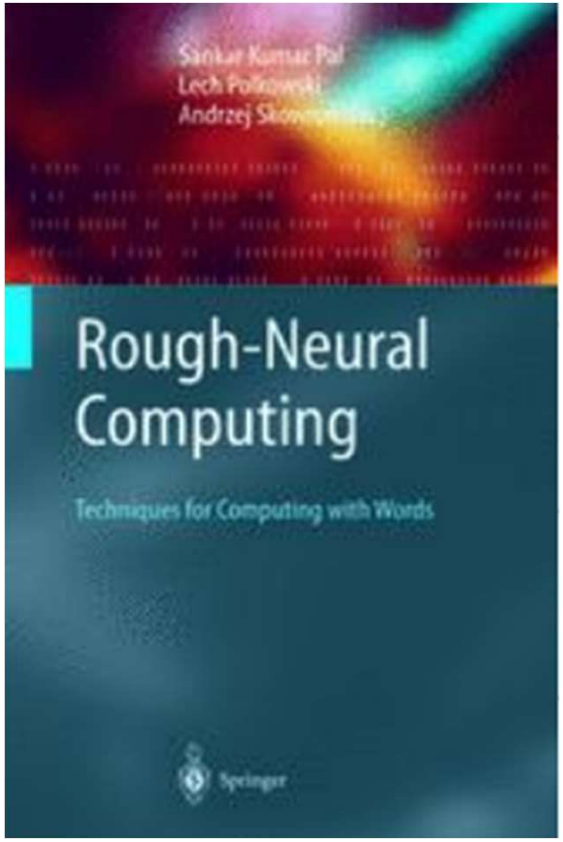
--- conflict resolution

…

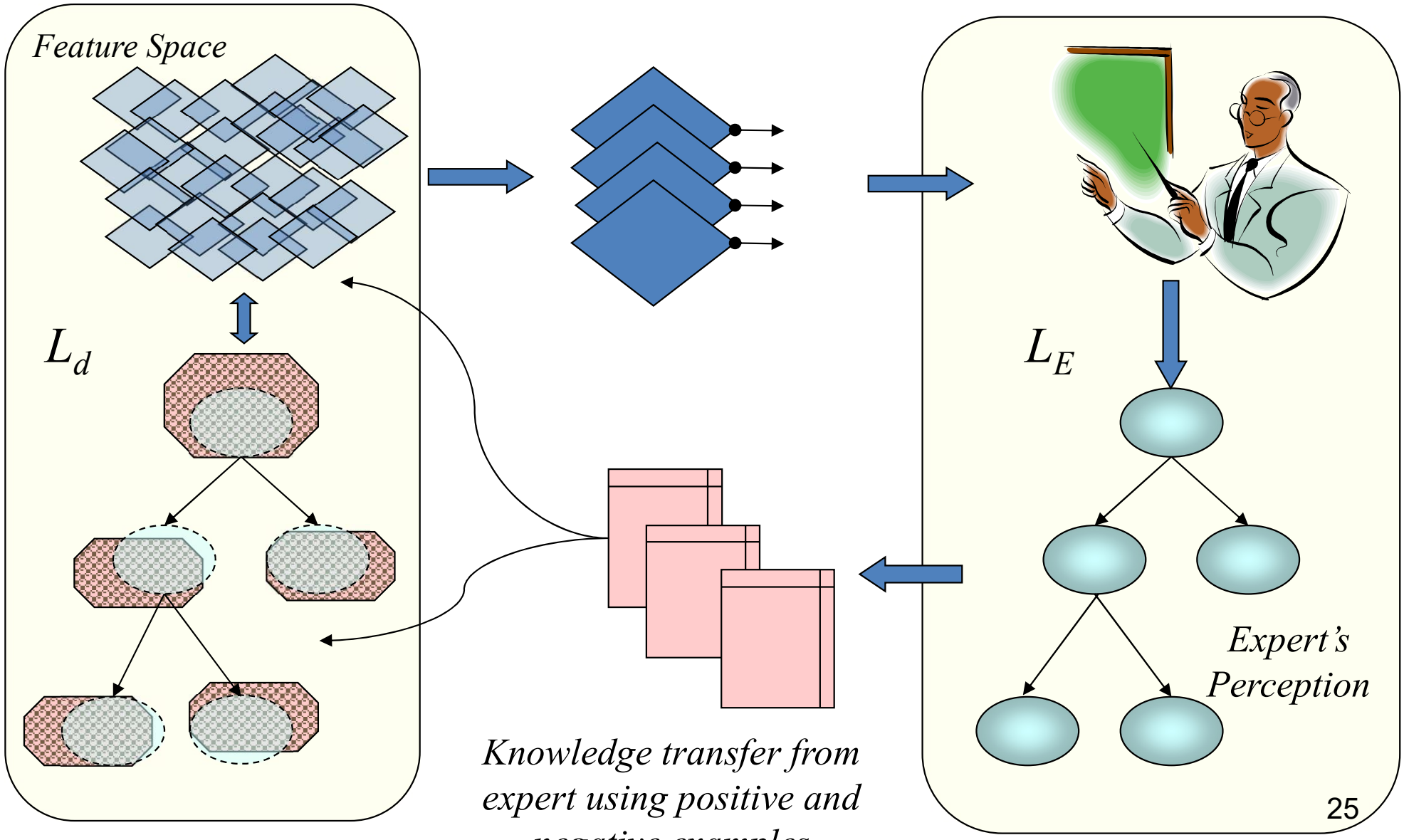
APPLICATIONS OF RS IN MANY AREAS

http://rsds.ur.edu.pl

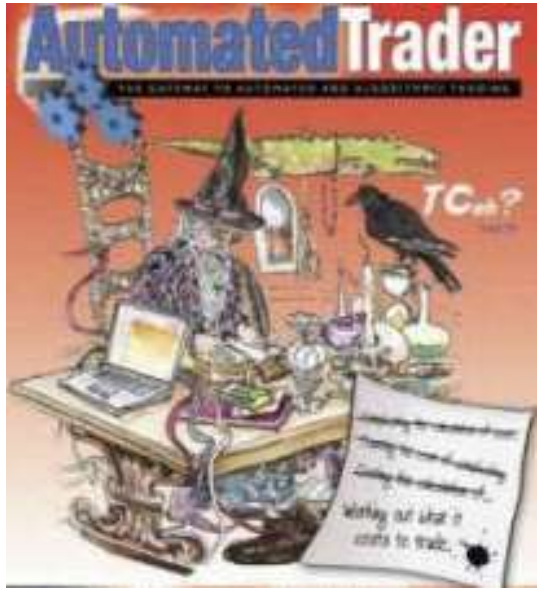
COMBINATION OF ROUGH SETS AND FUZZY SETS

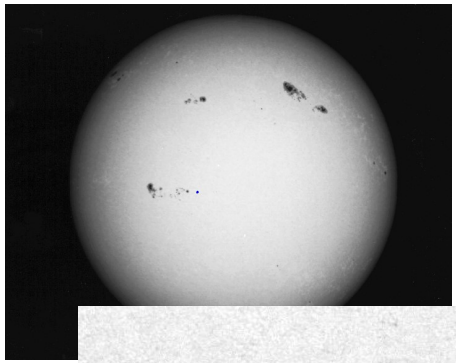


ROUGH SET BASED ONTOLOGY APPROXIMATION

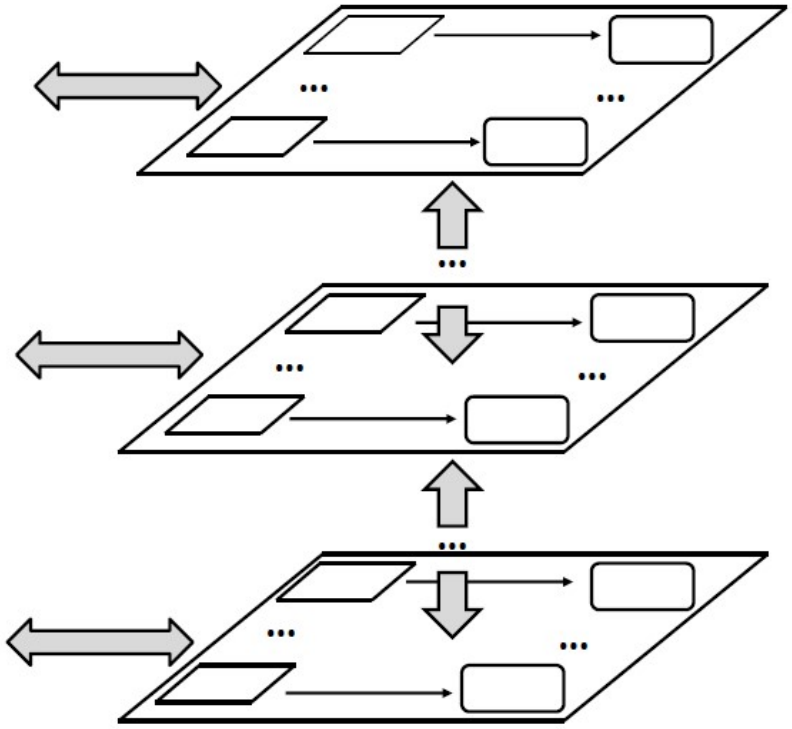


APPLICATIONS :
APROXIMATION OF COMPLEX VAGUE CONCEPTS





HIERARCHICAL STRUCTURES IN ABSTRACT MATHEMATICAL SPACES



i: $\mathcal{M}_i,\ L_i,\ \|=_i$

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

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

SCALABILITY

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

WHAT NEXT?

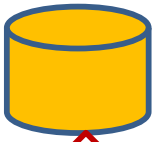
DO WE HAVE
THE RELEVANT COMPUTING MODEL
SUPPORTING

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

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

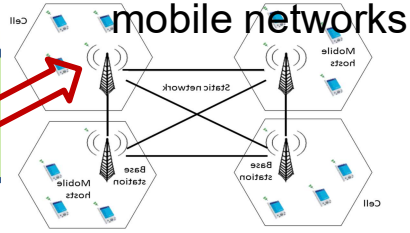
literature

interactions: dialogue, queries



pools of sensors,, robots, tools,…

Internet

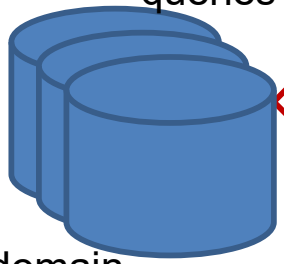


mobile networks

some interactions can be implemented through Internet, some through cellular (mobile) networks

interactions: dialogues, queries, …

Human-in-the loop, Human Centered AI



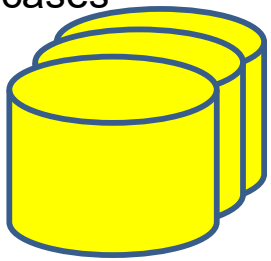
domain databases of cases

IS

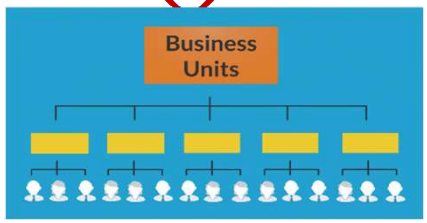
decision support in problem solving

interactions: dialogues, sensory measurements, actions, plans

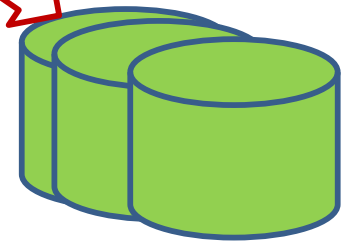
domain experts, domain centers different stakeholder groups, …



knowledge bases about particular units



business units



general knowledge bases, e.g., guides, laws, principles often expressed in natural language

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)

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

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.

GRANULES & PERCEPTION

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)

INTERACTIVE GRANULAR COMPUTING (IGrC)

=

GrC +

INTERACTIONS OF PHYSICAL OBJECTS +

PERCEPTION +

REASONING (JUDGMENT)

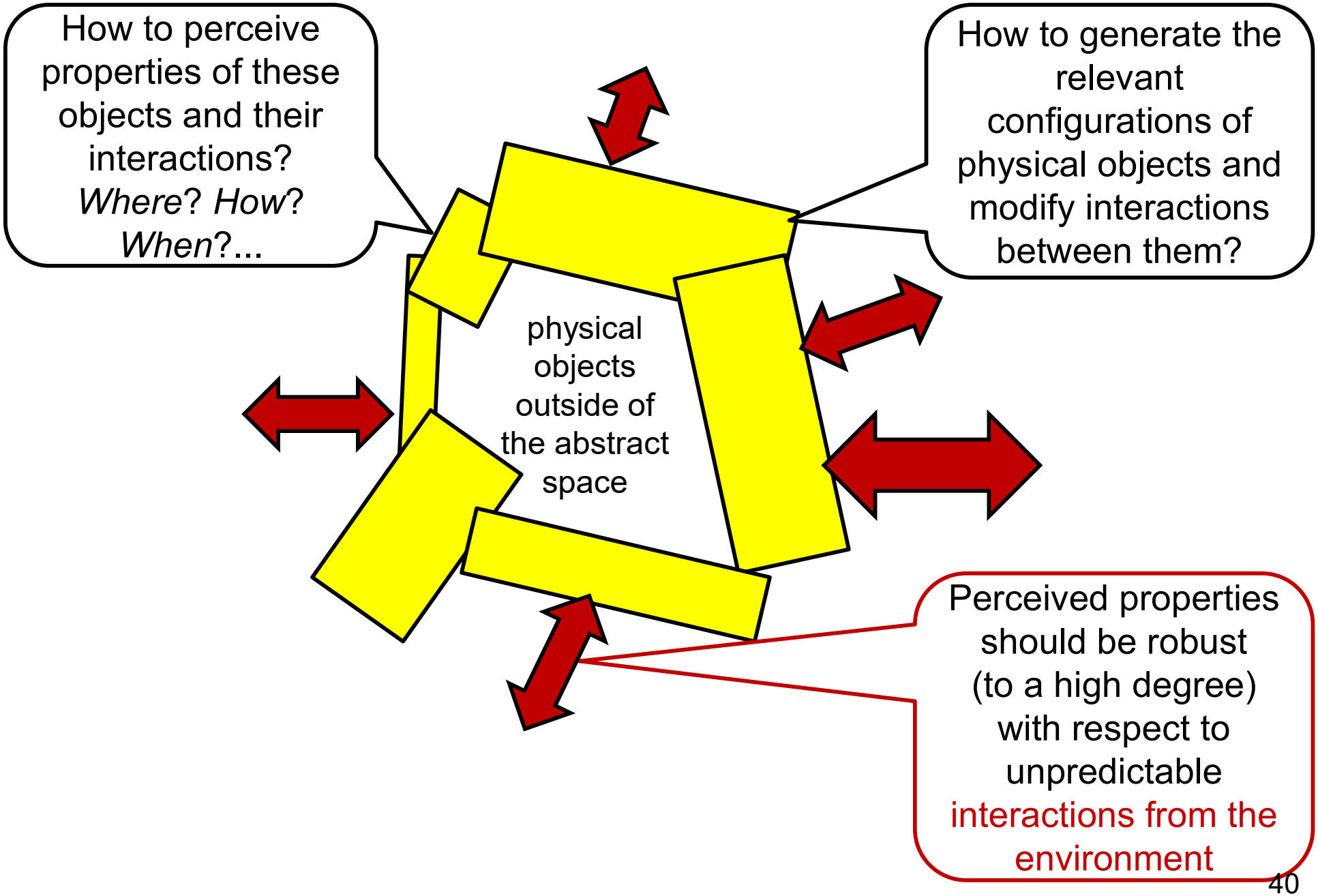
POSTULATES

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?
physical objects outside of the abstract space
Perceived properties should be robust (to a high degree) with respect to unpredictable interactions from the environment

COMPLEX GRANULES (C-GRANULES)

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

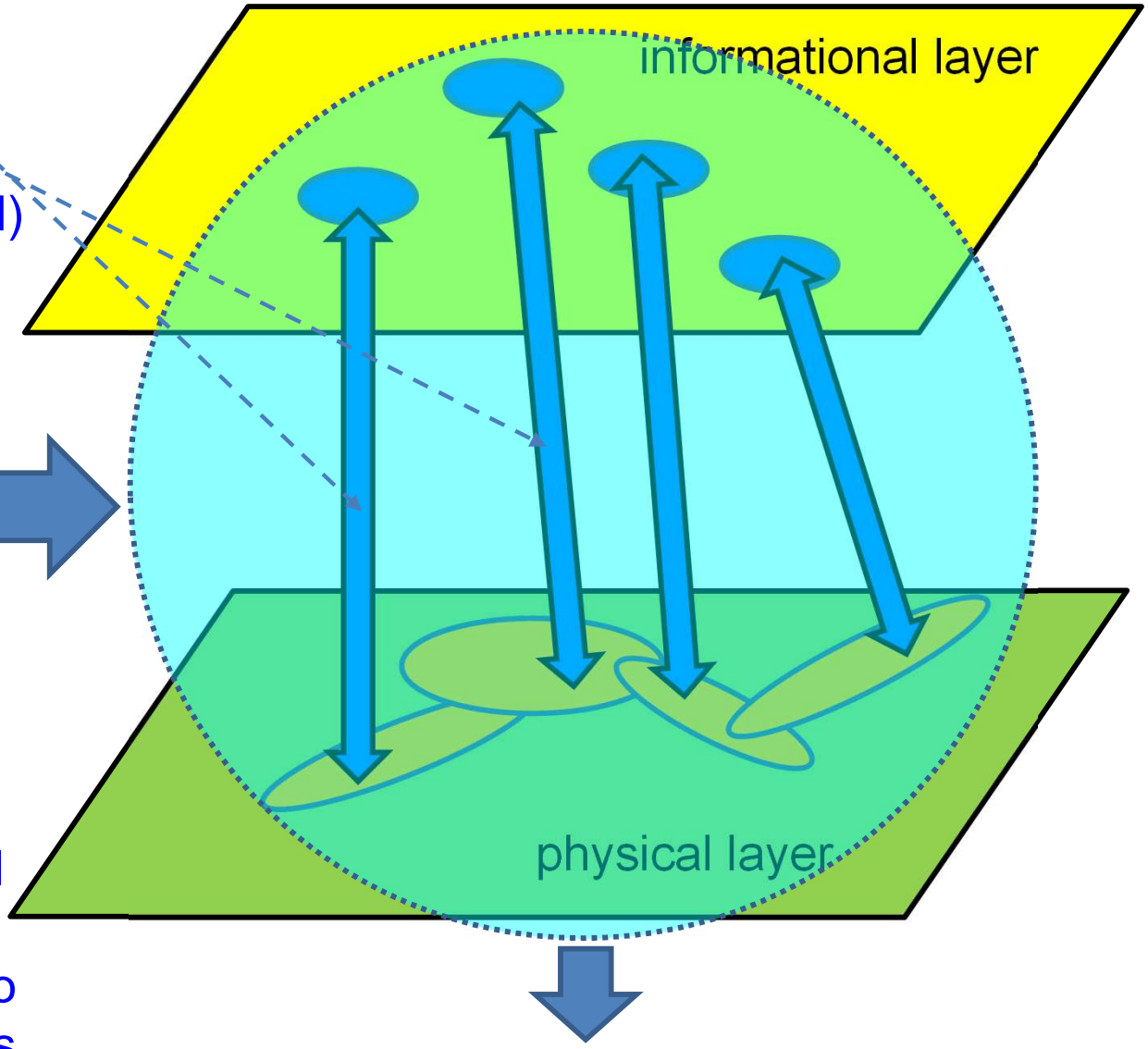
Special cases:

- *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)**

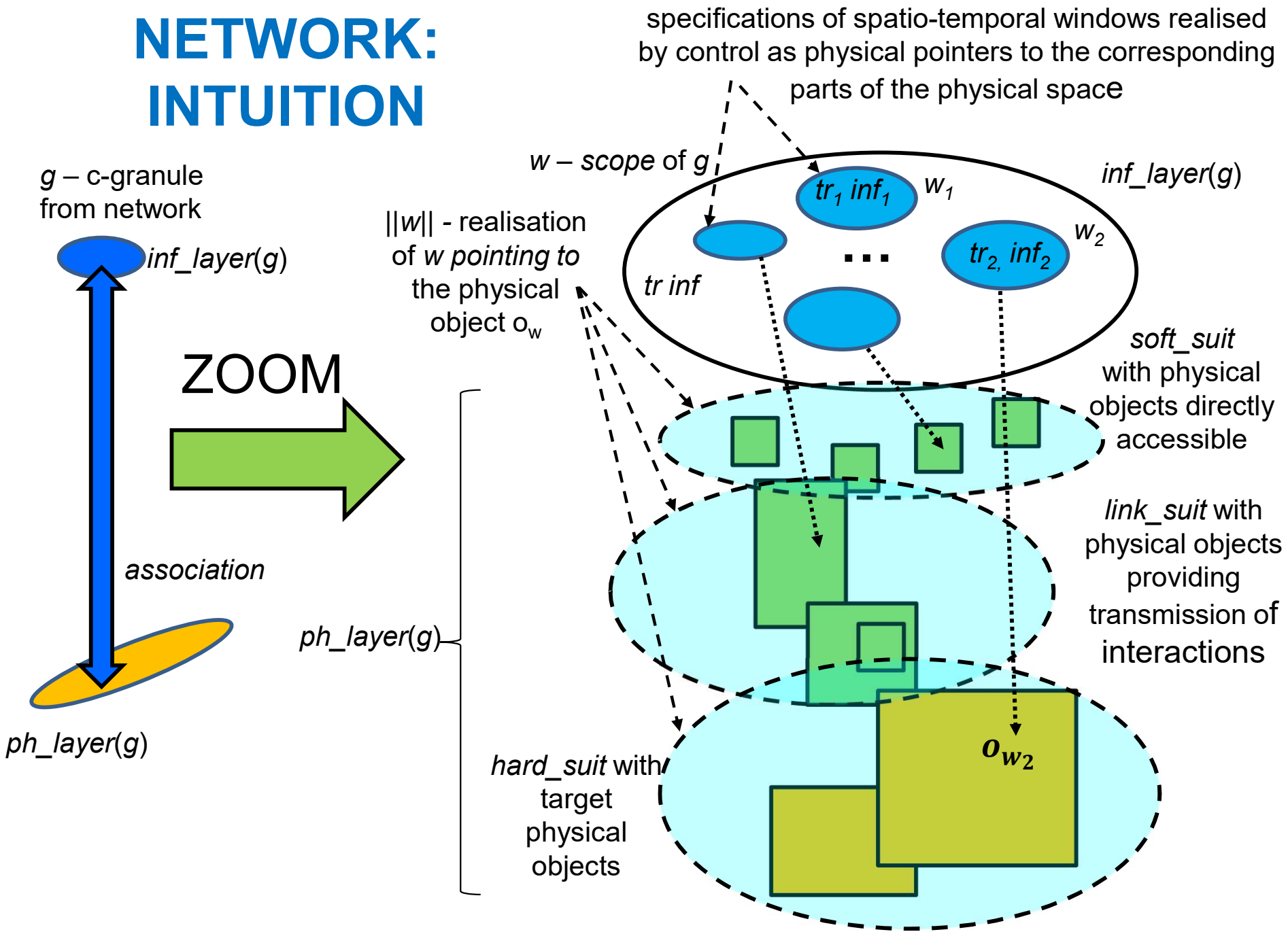
CONTROL of c-granule *tr*



Control is able to initiate 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.

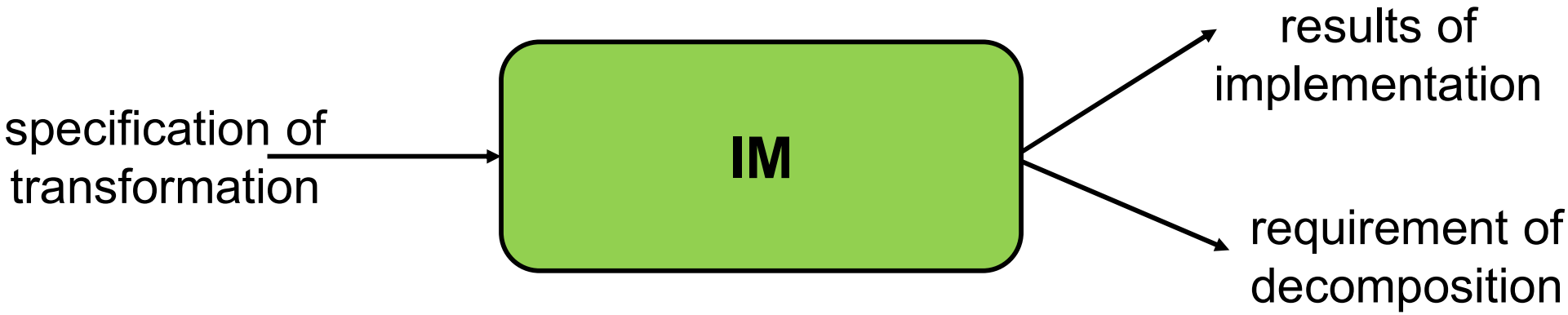
NETWORK OF INFORMATIONAL COMPLEX GRANULES DEALING WITH ABSTRACT AND PHYSICAL OBJECTS

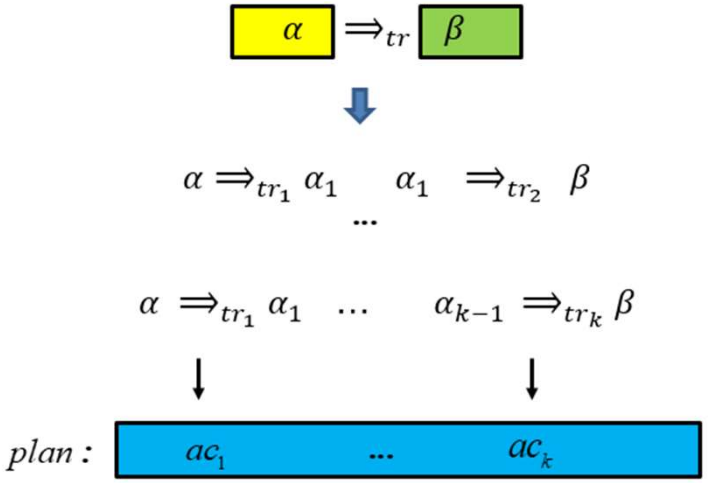
C-GRANULE FROM NETWORK: INTUITION



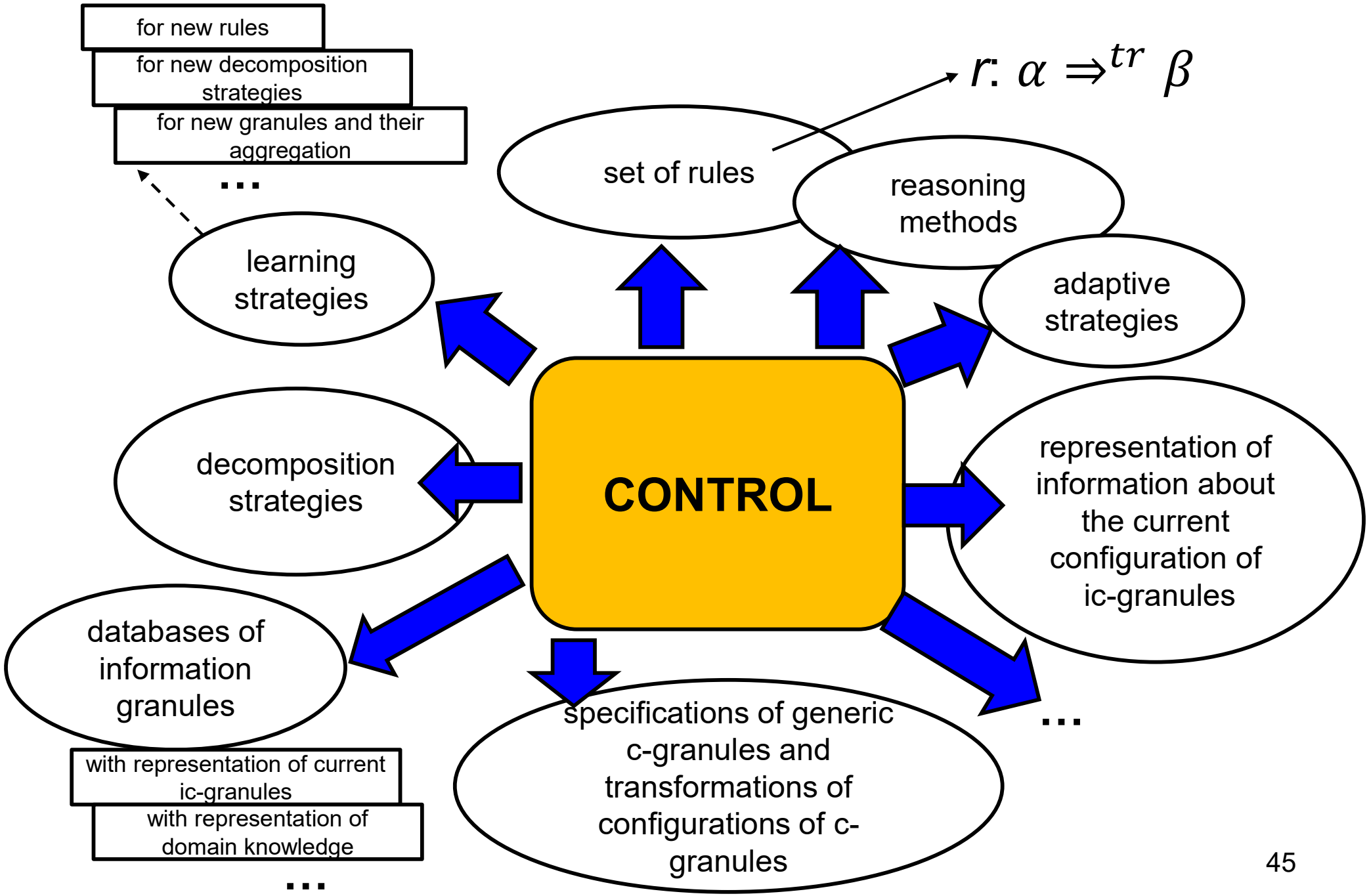
IMPLEMANTATIONAL MODULE (IM)

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

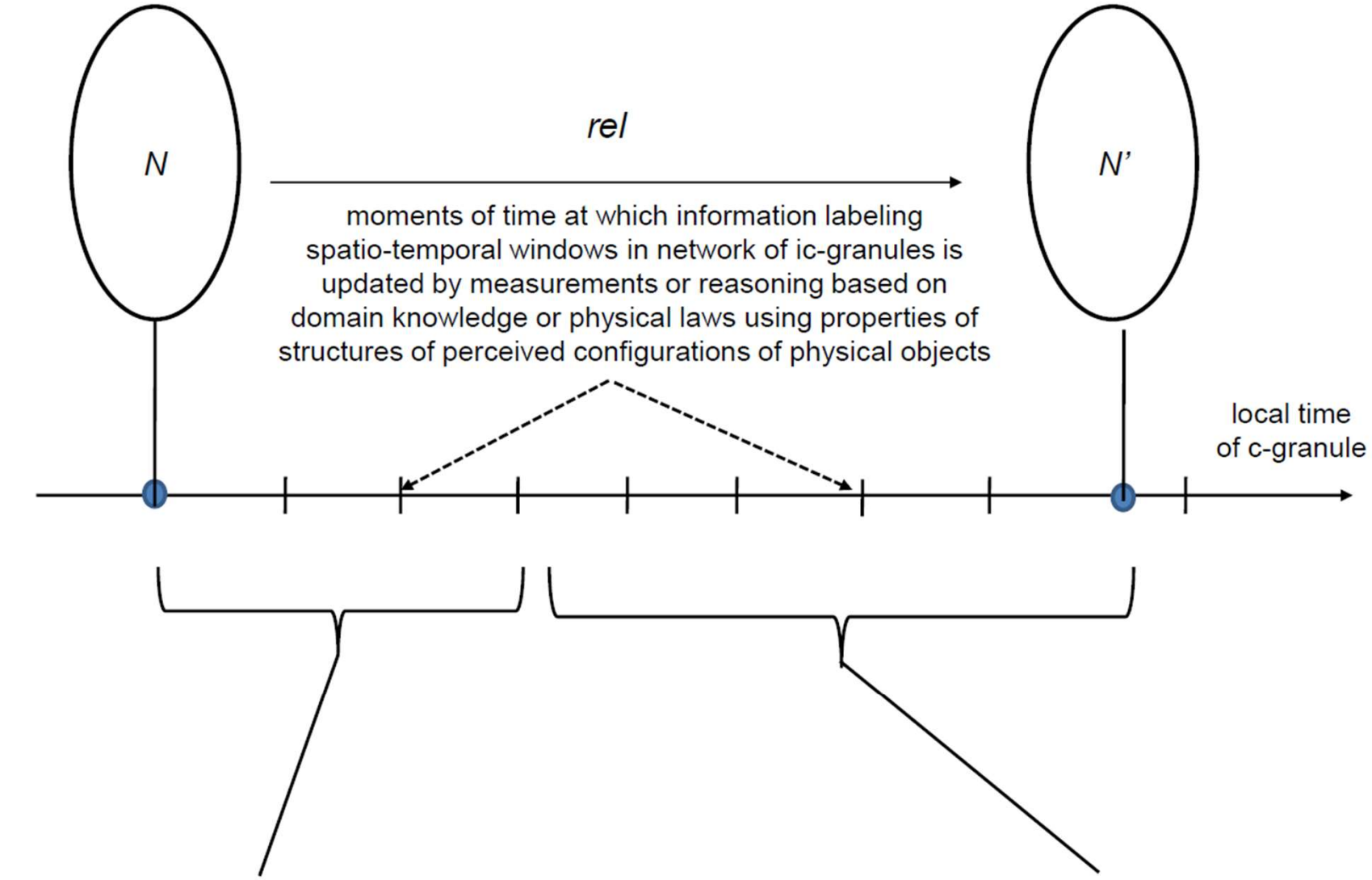




CONTROL: INTUITION



TRANSITON RELATION ON NETWORKS OF C-GRANULES



REASONING in IGrC realized by control of c-granules

LESLIE VALIANT: TURING AWARD 2010

.

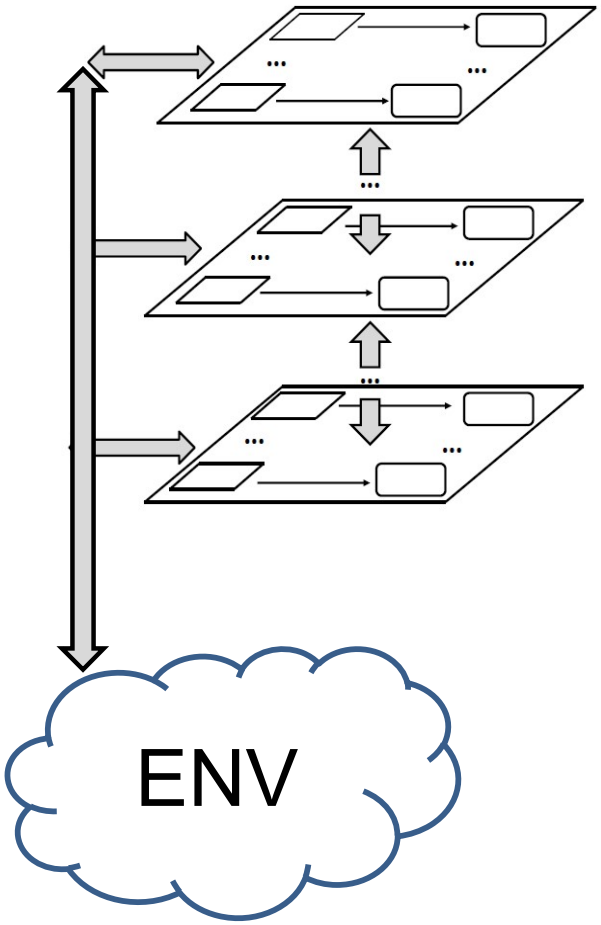
A specific challenge is to build on the success of machine learning so as to cover broader issues in intelligence.

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

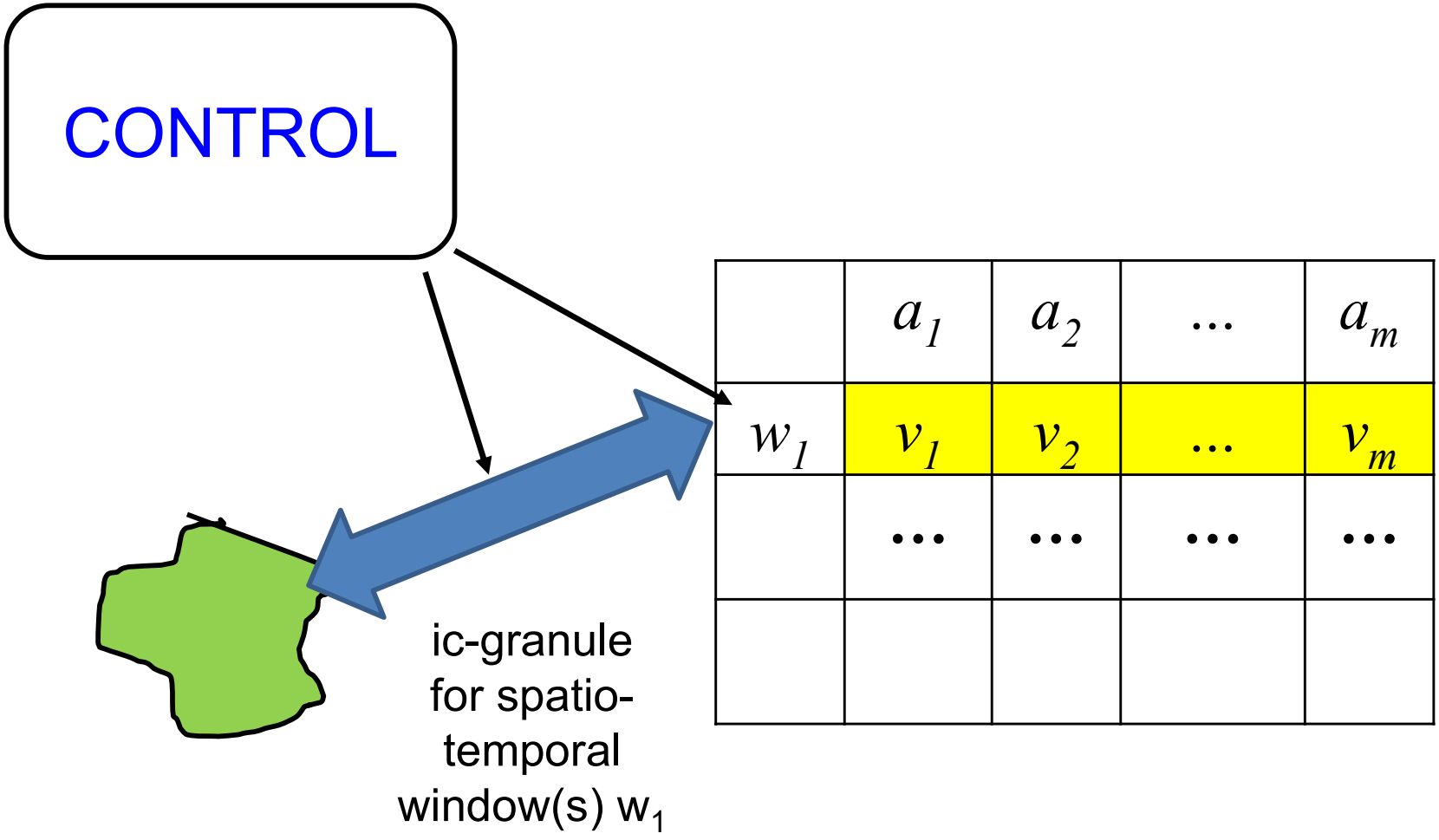


JUDGMENT SUPPORTING
- IN CONTINUOUS
INTERACTION WITH THE
PHYSICAL WORLD -
DISCOVERY OF
RELEVANT STRUCTURES
AND
COMPUTATIONAL BUILDING
BLOCKS (GRANULES) OVER
THEM FOR COGNITION

where, what, how, when,…

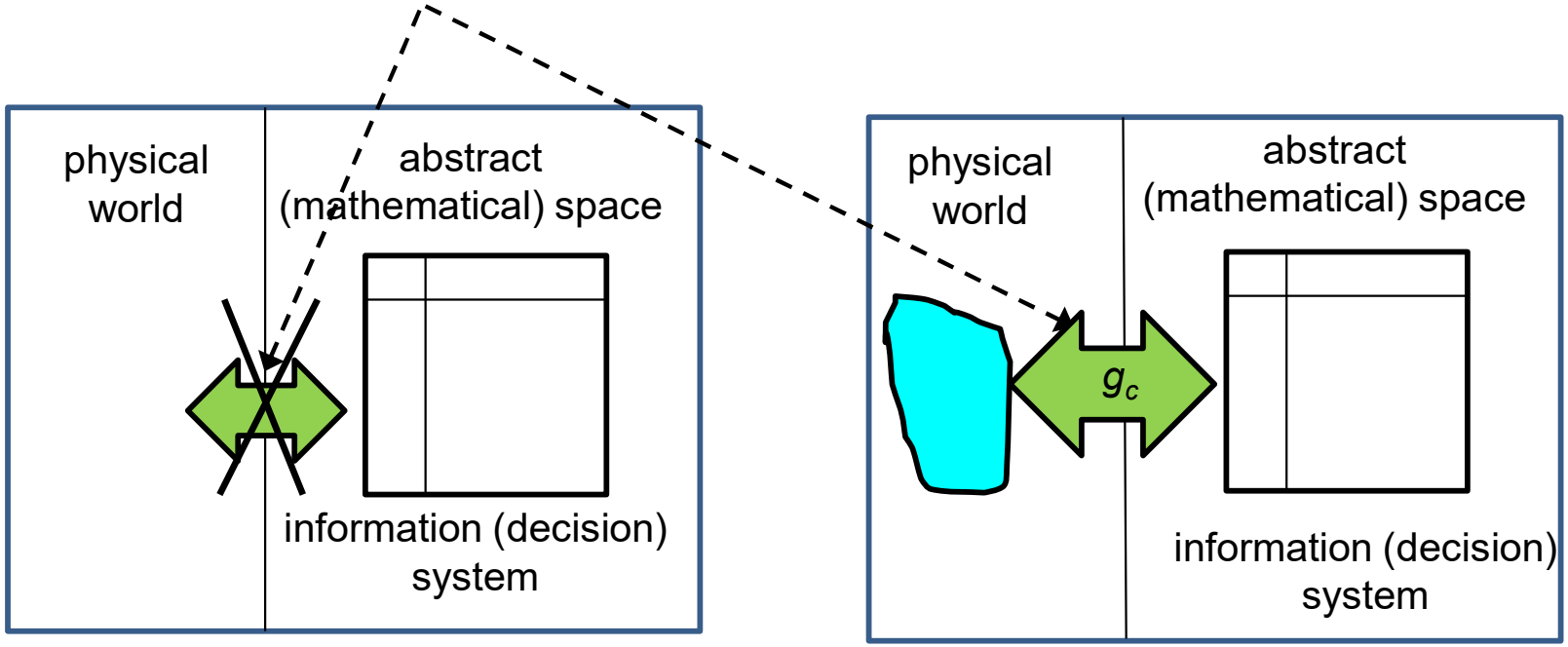
REASONING TOWARD ESTIMATON OF MEMBERSHIP: RS & FUZZY SETS (FS)

UNCERTAINTY IN OBJECT PERCEPTION
INDISCERNIBILITY RELATIONS



RS: PERCEPTUAL APPROACH

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.

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

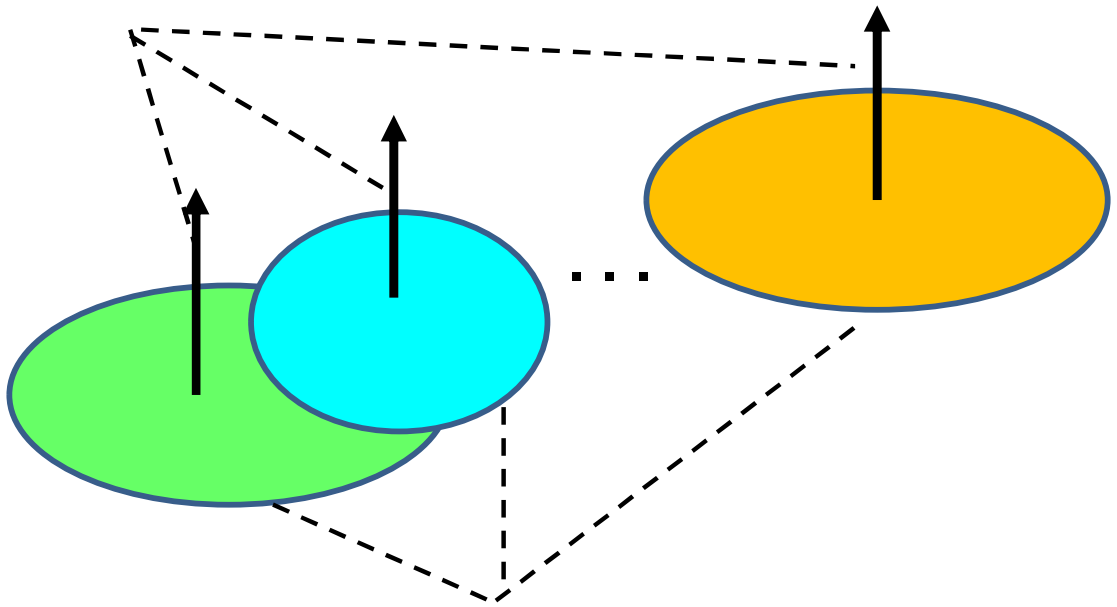
Necessary reasoning (judgment) methods supporting:

- 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

…

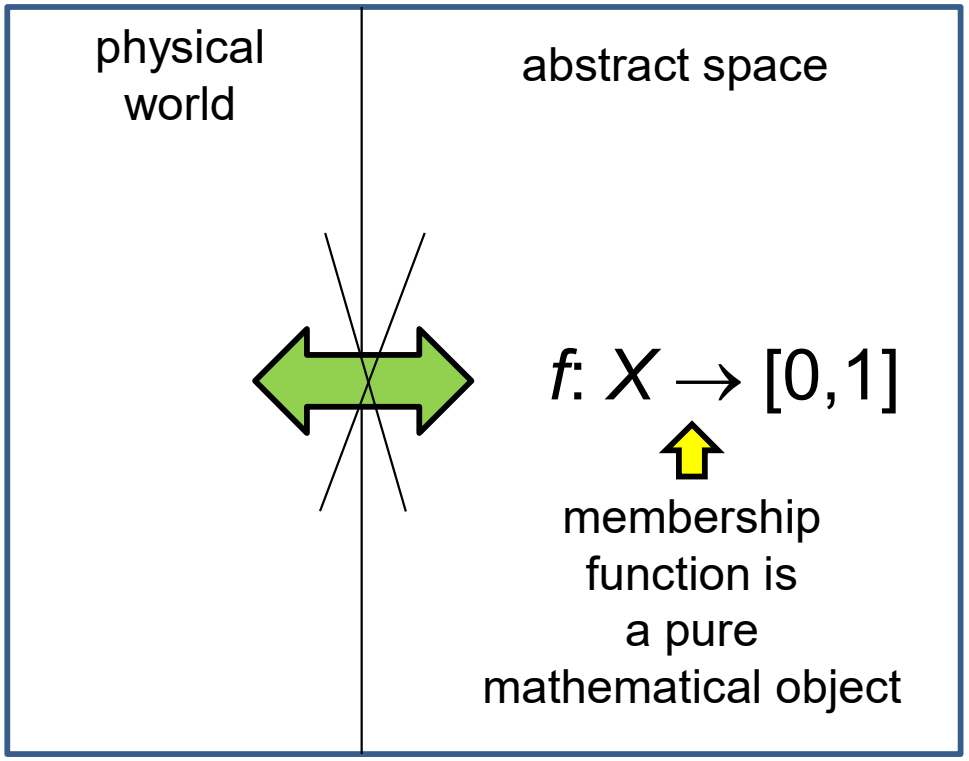
ADAPTIVE RS:
RULES FOR CHANGING COMPLEX GAMES

complex games for situations with the relevant properties

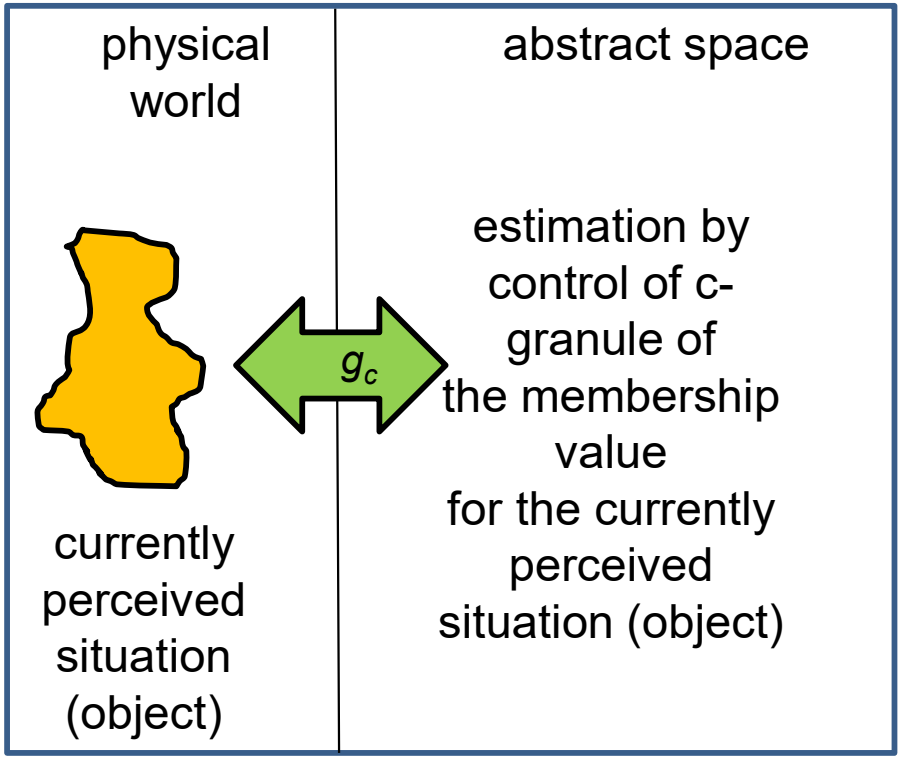


complex vague concepts
triggering complex games

FS : PERCEPTUAL APPROACH



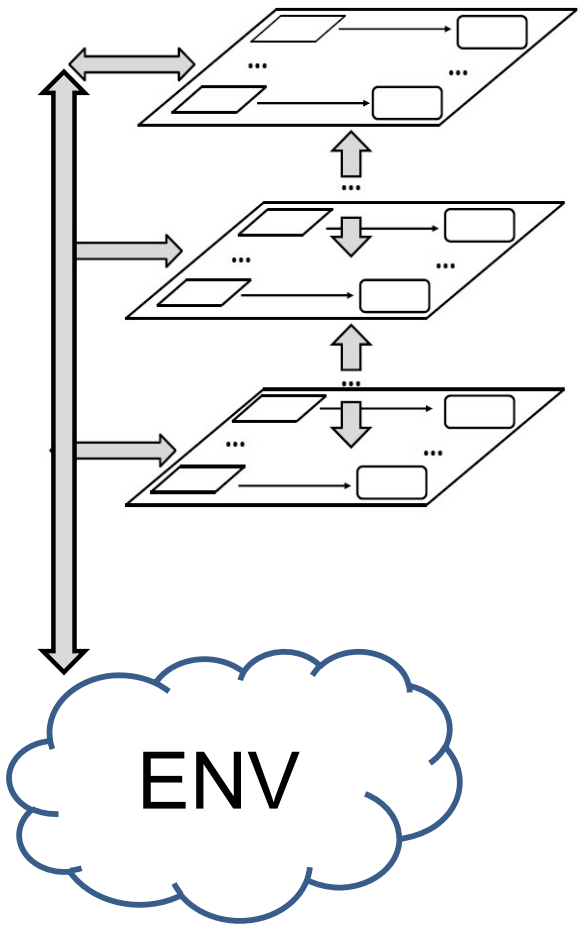
Fuzzy membership functions are pure mathematical objects.
According to Frederick Brooks their models (often models of vague concepts related to complex phenomena,) can not be constructed (induced) using traditional mathematical modeling.
Existing approaches to modeling of fuzzy membership functions should be enriched by mechanisms for continuous interaction with the physical real world for perception of the current situation making it possible to estimate membership values.



Fuzzy sets in IGrC: based on **physical semantics**: fuzzy membership value for the currently perceived situation in the real physical world is estimated on the basis of perceived data by networks of ic-granules dynamically interacting with the real physical world up to the moment when understanding of the perceived situation is satisfactory for making this estimation by control of c-granule.

RS AND COMPLEX PHENOMENA: WHAT NEXT?

REASONING ABOUT CHANGES: ROUGH CALCULUS



ROUGH SETS
IN INTELIGENT SYSTEMS
DEALING WITH COMPLEX PHENOMENA:

SPACE OF REASONING CONSTRUCTED
OVER DYNAMIC STRUCTURES BASED ON
INTERACTIVE GRANULAR COMPUTATIONS
(NOT PURELY MATHEMATICAL!)
AS
THE BASIS FOR APPROXIMATE REASONING,
IN PARTICULAR FOR CONCEPT
(CLASSIFICATION) APPROXIMATION IN
INTELLIGENT SYSTEMS

RS IN IS's DEALING WITH COMPLEX PHENOMENA

APPROXIMATIONS OF COMPLEX VAGUE CONCEPTS SHOULD BE DEFINED ON THE BASIS OF REASONING (JUDGMENT) OVER THESE DYNAMICALLY CHANGING STRUCTURES

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.

APPROXIMATION REGIONS

- inconsistency in data (considered now in rough sets)
- falsity regions (mistakes in prediction)
- not satisfactory reasoning tools for resolving conflicts in prediction of decisions (e.g. between arguments *for* and *against*)

IGrC BASED FOUNDATIONS FOR

IS's

RS

FUZZY SETS

CONTROL

RISK MANAGEMENT

DATA SCIENCE

COLLECTIVE INTELLIGENCE

INTELLIGENCE UNDERSTANDING

...

REASONING (JUDGMENT) ABOUT MEMBERSHIP IS PERFORMED ALONG COMPUTATIONS OVER NETWORKS OF C-GRANULES

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).

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

REASONING SUPPORTING PERCEPTION

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.

Alva Noë: Action in Perception, MIT Press 2004

SPECIAL ASPECTS OF NEW KIND OF ALGORITHMS: ML

The algorithms I discuss in this book are special. Unlike most algorithms, they can be run in environments unknown to the designer, and they learn by **interacting with the environment** how to act effectively in it. After sufficient **interaction** they will have expertise not provided by the designer, but extracted from the environment.

I call these algorithms **ecorithms**.

Leslie Valiant: Probably Approximately Correct. Nature's Algorithms for Learning and Prospering in a Complex World, MIT Press 2013

REASONING SUPPORTING BASIC CONTROL CYCLE

BASIC STEPS IN RS BASED REASONING IN IS's DEALING WITH COMPLEX PHENOMENA

GIVEN :

g_o - current state of perception

F_e - family of formal specifications of transformations of collections of ic-granules corresponding to enhancing information about the currently perceived situation

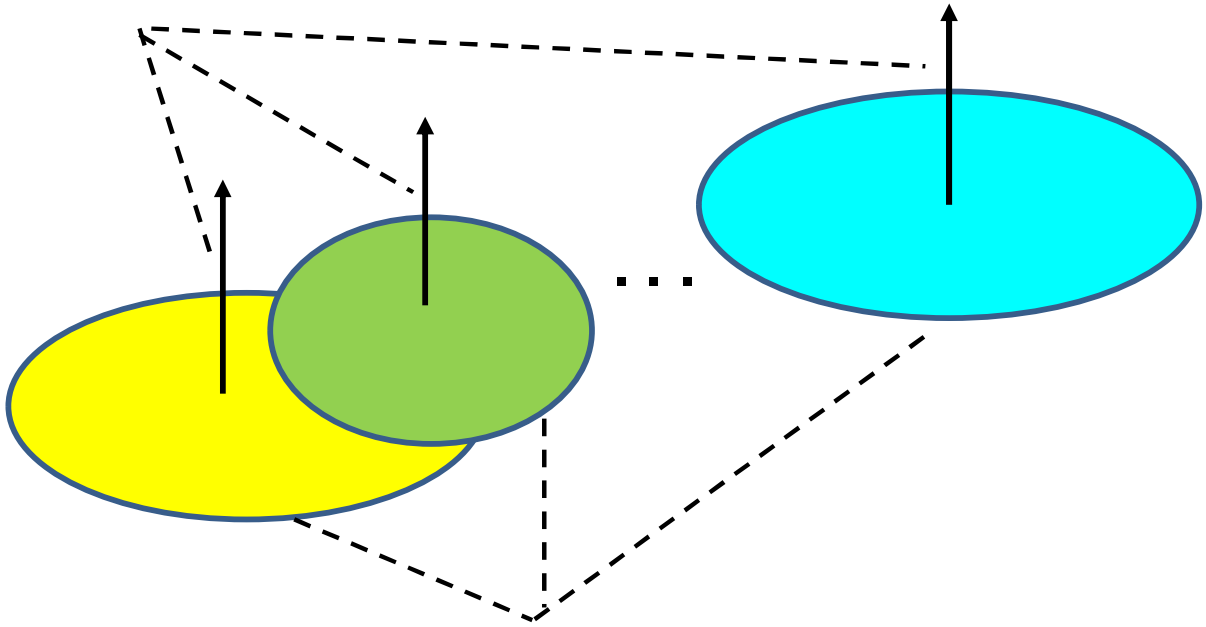
F_d - family of formal specifications of transformations of collections of ic-granules corresponding to decisions

BASIC CYCLE STEPS:

1. If g_o makes it possible to select the relevant decision then implement the corresponding decision transformation from F_d and update g_o with information perceived after implementation and go to Step 1;
2. Select *tr* from *F* and implement it in the physical world;
3. Enhance the current state of perception g_o by information obtained by perceiving the configuration of physical objects obtained by implementation of *tr;*
4. Go to Step 1.

INTELLIGENT SYSTEMS
IN DISCOVERING
OF COMPLEX GAMES AND THEIR EVOLUTION
IN THE CONTEXT OF
INTERACTING
THE ABSTRACT AND THE PHYSICAL WORLDS

actions/plans aiming to perform the relevant measurements/actions
toward achieving the target goals



complex vague concepts
triggering actions/plans

REASONING SUPPORTING SEARCHING FOR NEW RELEVANT DATA:

Where, what, when, How, …?

DATA GOVERNANCE

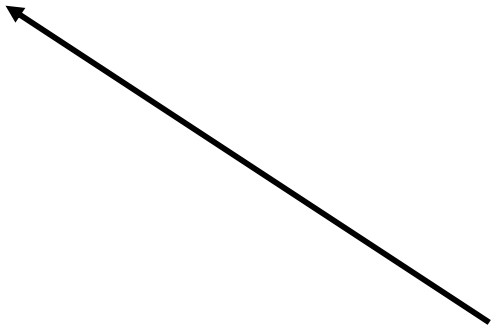
REASONING SUPPORTING IMPLEMENTATION OF ROBUST NETWORKS OF C-GRANULES

Niches in:

J. H. Holland, ”Signals and Boundaries. Building Blocks for Complex Adaptive Systems”, The MIT Press, Cambridge, MA (2014)

REASONING SUPPORTING ADAPTATION

power of judging rightly and following the soundest course of action, based on knowledge, experience, understanding, …
Webster's New World College Dictionary

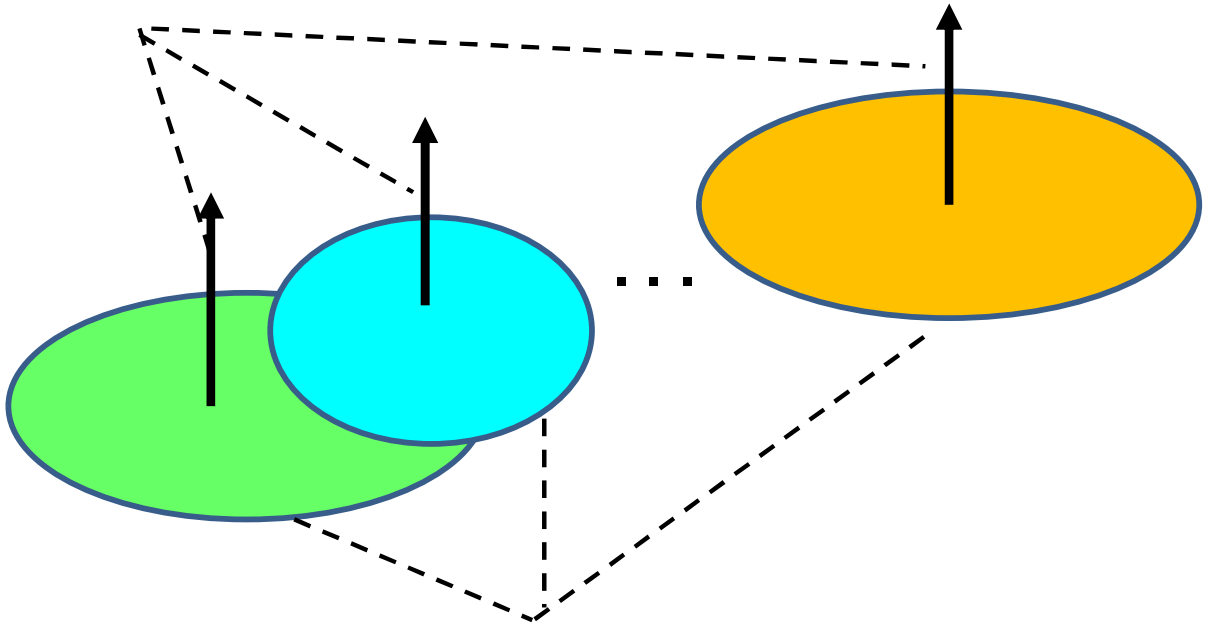


Aristotle's man of practical **wisdom**, the phronimos, does not ignore rules and models, or dispense
justice without criteria. He is observant of principles and, at the same time, open to their modification. He begins with nomoi – established law – and employs practical wisdom to determine how it should be applied in particular situations and when departures are warranted. Rules provide the guideposts for inquiry and critical reflection.

Leslie Paul Thiele: The Heart of Judgment Practical Wisdom, Neuroscience, and Narrative. Cambridge University Press 2006

INTELLIGENT SYSTEMS IN DISCOVERING OF COMPLEX ADAPTIVE GAMES IN THE CONTEXT OF INTERACTING THE ABSTRACT AND THE PHYSICAL WORLDS

complex games for situations with the relevant properties



complex vague concepts
triggering complex games

EXPERIENCE BASED RASONING

HUMAN-IN-THE-LOOP REASONING

HUMAN-CENTERED AI

PHENOMENOLOGY
originated by Edmund Husserl
as a method for exploring the nature of human experience and perception

Husserl was frustrated by the idea that science and mathematics were increasingly conducted on an abstract plane [treating nature itself as a mathematical manifold] that was disconnected from human experience and human understanding, independently of questions of truth and applicability. He felt that the sciences increasingly dealt with idealized entities and internal abstractions a world apart from the concrete phenomena of daily life.

Dourish, P.: Where the Action Is. The Foundations of Embodied Interaction. The MIT Press (2004)

PRACTICAL JUDGMENT

Practical judgment is not algebraic calculation. Prior to any deductive or inductive reckoning, the judge is involved in selecting objects and relationships for attention and assessing their interactions. Identifying things of importance from a potentially endless pool of candidates, assessing their relative significance, and evaluating their relationships is well beyond the jurisdiction of reason

Leslie Paul Thiele: The Heart of Judgment Practical Wisdom, Neuroscience, and Narrative. Cambridge University Press 2006

MELANIE MITCHELL

Santa Fe Institute

The quest for machines that can make abstractions and analogies is as old as the AI field itself, but the problem remains almost completely open.

Melanie Mitchell: Abstraction and Analogy-Making in Artificial Intelligence, Annals Reports of the New York Academy of Sciences 1505(1) 79-101 (2021)

We do not have yet formal reasoning for experience based reasoning working in IS's

However,

IS's on the basis of data analysis can help domain expert in his kind of reasoning.

Human experts can help AI's to improve reasoning, e.g., in inducing classifiers.

Human-Centered AI, Human-in-the-Loop ML

DECOMPOSITION OF VAGUE SPECIFICATIONS USING HUMAN BASED INFORMATION GRANULATION FOR DIVIDE AND CONQUER STRATEGY

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

DECOMPOSITION OF TRANSFORMATION SPECIFICATION

Transformation specification *tr* from an ic-granule with property α to an ic-granule with property β available at the planner ic-granule g_0

$$\alpha : g_0 \Rightarrow_{tr} \beta : g$$

$$\propto: g_o \Rightarrow_{tr_1} \alpha_1: g_1 \quad \alpha_1: g_1 \Rightarrow_{tr_2} \beta: g$$

$$\dots$$

$$\propto: g_o \Rightarrow_{tr_1} \alpha_1: g_1 \quad \dots \quad \alpha_{k-1}: g_{k-1} \Rightarrow_{tr_k} \beta: g$$

COMPUTING WITH WORDS
LOTFI A. ZADEH

[…] Manipulation of perceptions plays a key role in human recognition, decision and execution processes. As a methodology, computing with words provides a foundation for a computational theory of perceptions - a theory which may have an important bearing on how humans make - and machines might make – perception - based rational decisions in an environment of imprecision, uncertainty and partial truth.

[…] computing with words, or CW for short, is a methodology in which the objects of computation are words and propositions drawn from a natural language.

Lotfi A. Zadeh: From computing with numbers to computing with words – From manipulation of measurements to manipulation of perceptions. IEEE Transactions on Circuits and Systems 45(1), 105–119 (1999)

DIALOGUE OF IS's WITH DOMAIN EXPERTS OR USERS

JUDEA PEARL - TURING AWARD 2011

for fundamental contributions to artificial intelligence through the development of a calculus for probabilistic and causal reasoning.

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*.

Judea Pearl: Causal inference in statistics: An overview. Statistics Surveys 3, 96-146 (2009)

REASONING SUPPORTNG DISCOVERY OF SOCIETIES OF C-GRANULES WITH THE REQUIRED BEHAVIORAL PATTERNS

SUMMARY

We outlined some aspects of RS & GrC and PERCEPTUAL APPROACH TO INTELLIGENT SYSTEMS BASED ON IGrC.

We discussed
IGrC model
as the base for design
Intelligent Systems
dealing with complex phenomena.

The aim was to explain how the IGrC computing model has the potential to handle the grounding problem by bridging a connection between the abstract mathematical modeling and the real physical semantics.

We discussed some aspects of modeling of reasoning (ADAPTIVE) JUDGMENT on which the decision support systems dealing with complex phenomena should be based.

FOUNDATIONS BASED ON IGrC FOR INTELLIGENT SYSTEMS DEALING WITH COMPLEX PHENOMENA

Tomorrow, I believe, we will use
INTELLIGENT SYSTEMS
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.

Warm gratitude for cooperation, friendship, support

Piotr Artiemjew, Jan Bazan, Mohua Banerjee, Hans Dieter Burkhard, Mihir K. Chakraborty, Gianpiero Cattaneo, Davide Ciucci, Ludwik Czaja, Andrzej Czyżewski, Rafał Deja, Ivo Duentsch, Soma Dutta, Anna Gomolińska, Grzegorz Góra, Paweł Gora, Salwatore Greco, Marek Grzegorowski, Jerzy Grzymała-Busse, Jiming Liu, Hung Son Nguyen, Sinh Hoa Nguyen, Tuan Trung Nguyen, Ngoc Thanh Nguyen, Andrzej Jankowski, Janusz Kacprzyk, Jan Komorowski, Bożena Kostek, Jan Krempa†, Rafał Latkowski, Pawan Lingras, Stan Matwin, Pradipta Maji, Duoqian Miao, Misza Moshkov, Sławomir Nowak†, Agnieszka Nowak-Brzezińska, Piero Pagliani, Sankar K. Pal, Gheorghe Păun, Witold Pedrycz, James Peters, Alberto Pettorossi, Lech Polkowski, Małgorzata Przybyła-Kasperek, Sheela Ramanna, Zbigniew Raś, Cecylia Rauszer†, Ewa Orłowska, Grzegorz Rozenberg, Henryk Rybiński, Roman Słowiński, Peter Starke†, Jerzy Stefanowski, Jarosław Stepaniuk, Zbigniew Suraj, Andrzej Szałas, Piotr Synak, Marcin Szczuka, Dominik Ślęzak, Roman Swiniarski†, Tomasz Szmuc, Alicja Wakulicz-Deja, Shusaku Tsumoto, Guoyin Wang, Piotr Wasilewski, Arkadiusz Wojna, Marcin Wojnarski, Marcin Wolski, Jakub Wróblewski, Hong Yu, Lotfi A. Zadeh†, Sławomir Zadrożny, Ning Zhong, Beata Zielosko, JingTao Yao, T.Y. Lin, YiYu Yao, **…**

THANK YOU!