ROUGH SETS: FROM RUDIMENTS TO CHALLENGES

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AGENDA

RUDIMENTS OF ROUGH SETS

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CHALLENGES FOR INTERACTIVE COMPUTATIONAL SYSTEMS (ICS):

GRANULARITY OF INFORMATION

VAGUENESS

INTERACTIONS

ADAPTIVE JUDGMENT

HIERARCHICAL LEARNING

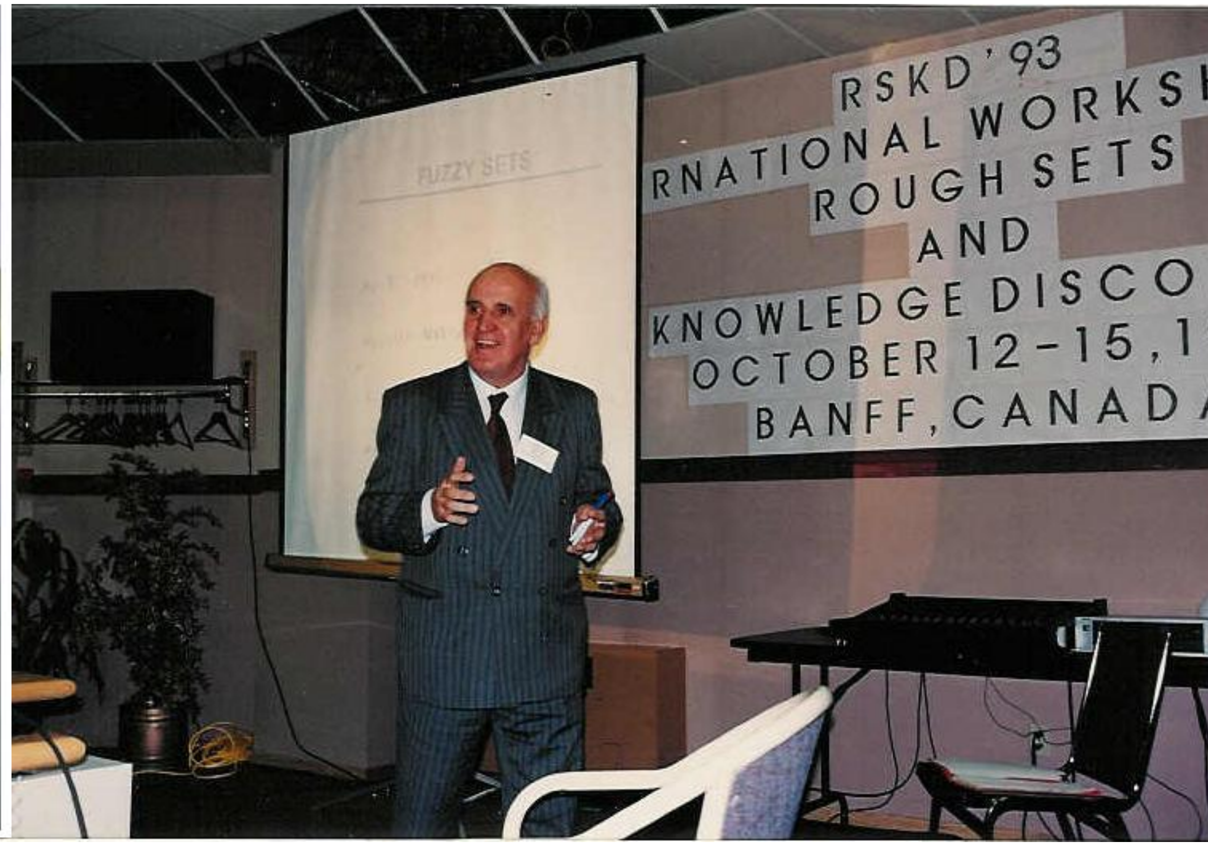
CONTROL & RISK MANAGEMENT IN ICS

LIST OF CHALLENGES

RUDIMENTS OF 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)



Now thousands of papers http://rsds.univ.rzeszow.pl/

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)

RUDIMENTS OF ROUGH SETS

- One of the main goals of the rough set analysis is construction of concept descriptions and induction of concept approximations.
- In particular, rough set theory constitutes a sound basis for KDD. It offers methods for:
  - discovering patterns hidden in data
  - for feature selection, feature extraction, data reduction, decision rule generation, pattern extraction (templates, association rules) etc.
  - extraction partial or total dependencies from data elimination of redundant data
  - dealing with null values, missing data
  - dealing with incremental data and others.

RUDIMENTS OF ROUGH SETS

- **Basic Concepts of Rough Sets**
- **Relationships with other approaches**
- **Rough Sets and Boolean Reasoning**

BASIC CONCEPTS OF ROUGH SETS

- Information/Decision Systems (Tables)
- Indiscernibility and Discernibility
- Set Approximation
- Reducts and Core
- Rough Membership
- Dependency of Attributes
- Decision Rules

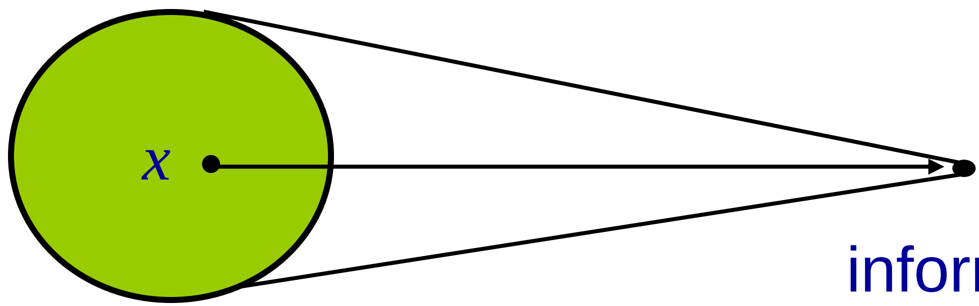
INDISCERNIBILITY RELATIONS

infromation system
(data table)

	a_1	a_2	…	a_m	d
x_1	v_1	v_2	…	v_m	1
	…	…	…	…	…

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

τ



$u=Inf_A(x)$

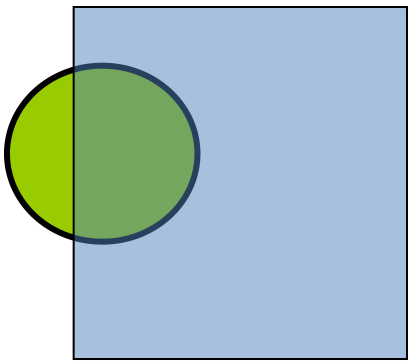
information signature of ***x***

neighborhood of x

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

τ

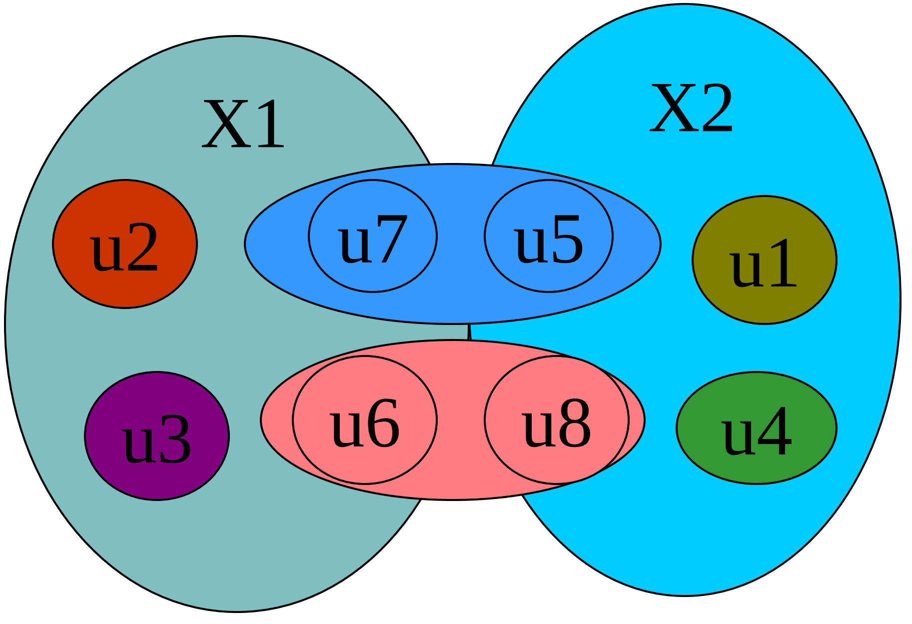
tolerance or similarity



DISCERNIBILITY

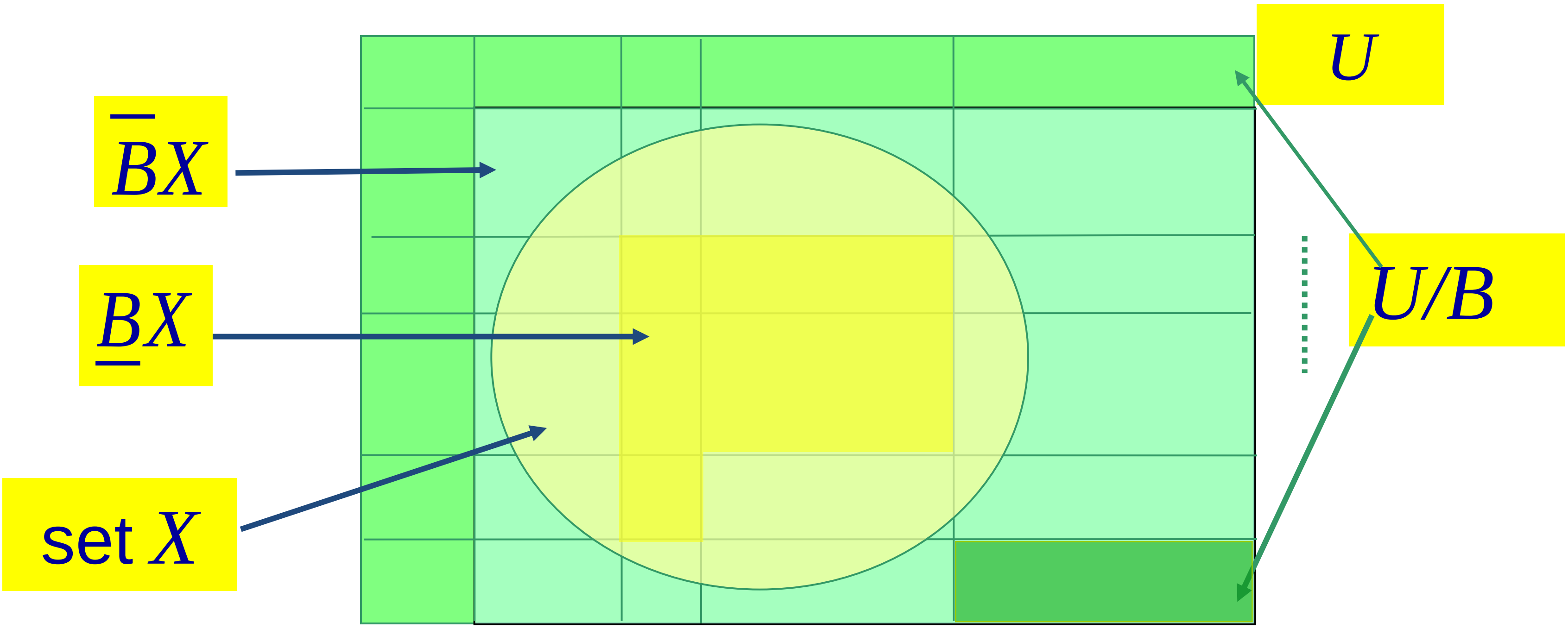
$$x DIS_{IS}(B) y \text{ iff } non(x IND_{IS}(B)) y$$

However, this is only the simplest case!


X1
X2
u2
u7
u5
u1
u3
u6
u8
u4

LOWER AND UPPER APROXIMATION

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



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

PROPERTIES OF APPROXIMATIONS

$$\underline{B}(X) \subseteq X \subseteq \overline{B}X$$

$$\underline{B}(\phi) = \overline{B}(\phi) = \phi, \underline{B}(U) = \overline{B}(U) = U$$

$$\overline{B}(X \cup Y) = \overline{B}(X) \bigcup \overline{B}(Y)$$

$$\underline{B}(X \cap Y) = \underline{B}(X) \cap \underline{B}(Y)$$

$$X \subseteq Y \text{ implies } \underline{B}(X) \subseteq \underline{B}(Y) \text{ and } \overline{B}(X) \subseteq \overline{B}(Y)$$

PROPERTIES OF APPROXIMATIONS

$$\underline{B}(X \cup Y) \supseteq \underline{B}(X) \cup \underline{B}(Y)$$

$$\overline{B}(X \cap Y) \subseteq \overline{B}(X) \cap \overline{B}(Y)$$

$$\underline{B}(-X) = -\overline{B}(X)$$

$$\overline{B}(-X) = -\underline{B}(X)$$

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

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

where -*X* denotes *U* - *X*.

GENERALIZED APPROXIMATION SPACES

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

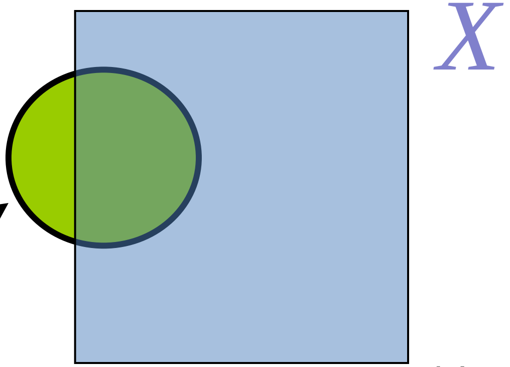
$$AS = (U, N, \nu)$$

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

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

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

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

ROUGH MEREOLOGY

MEREOLOGY

St. LEŚNIEWSKI (1916)

x is_a_ part_of y

ROUGH MEREOLOGY

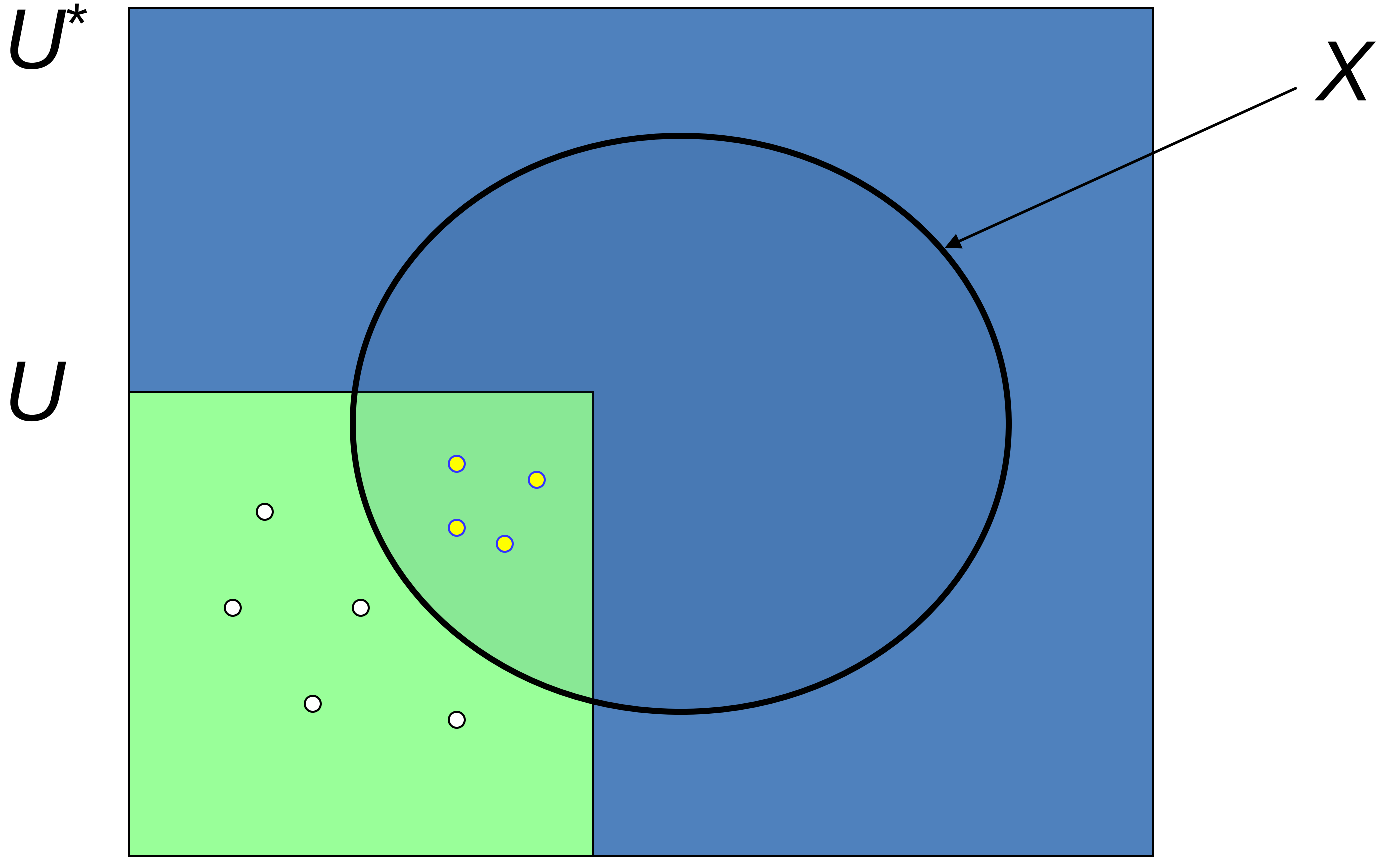
L. Polkowski and A. Skowron (1994-…)

x is_a_ part_of y in a degree

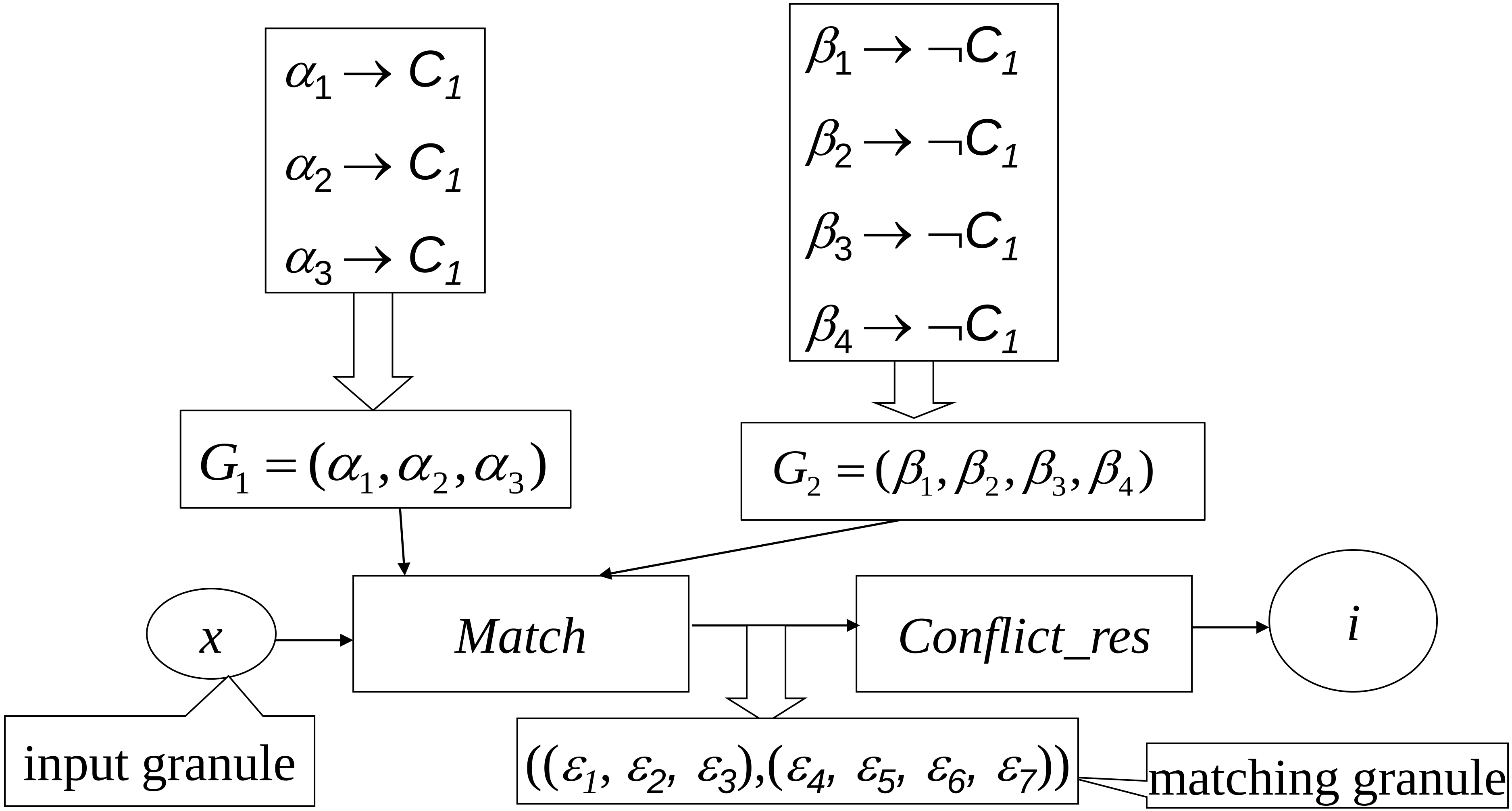
L. Polkowski, A. Skowron, Rough mereology, ISMIS'94, LNAI 869, Springer, 1994, 85-94

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

EXTENSIONS OF APPROXIMATIONS



APPROXIMATION EXTENSIONS: CLASSIFIERS



Conflict_res (Match(x,G_1,G_2))

ACCURACY OF APPROXIMATION

$$\alpha_B(X) = \frac{|\underline{B}(X)|}{|\overline{B}(X)|}$$

where |X| denotes the cardinality of $X \neq 0.$

Obviously $0 \leq \alpha_B \leq 1.$

If $\alpha_B(X) = 1,$ *X* is *crisp* with respect to *B*.

If $\alpha_B(X) < 1,$ *X* is *rough* with respect to *B.*

POSITIVE REGION OF DECISION SYSTEM *T=(U,A,d)*

For any $C \subseteq A$ we define the *C*-positive region of *d*:

$$POS_C(d) = \bigcup_{X \in U/d} \underline{C}X$$

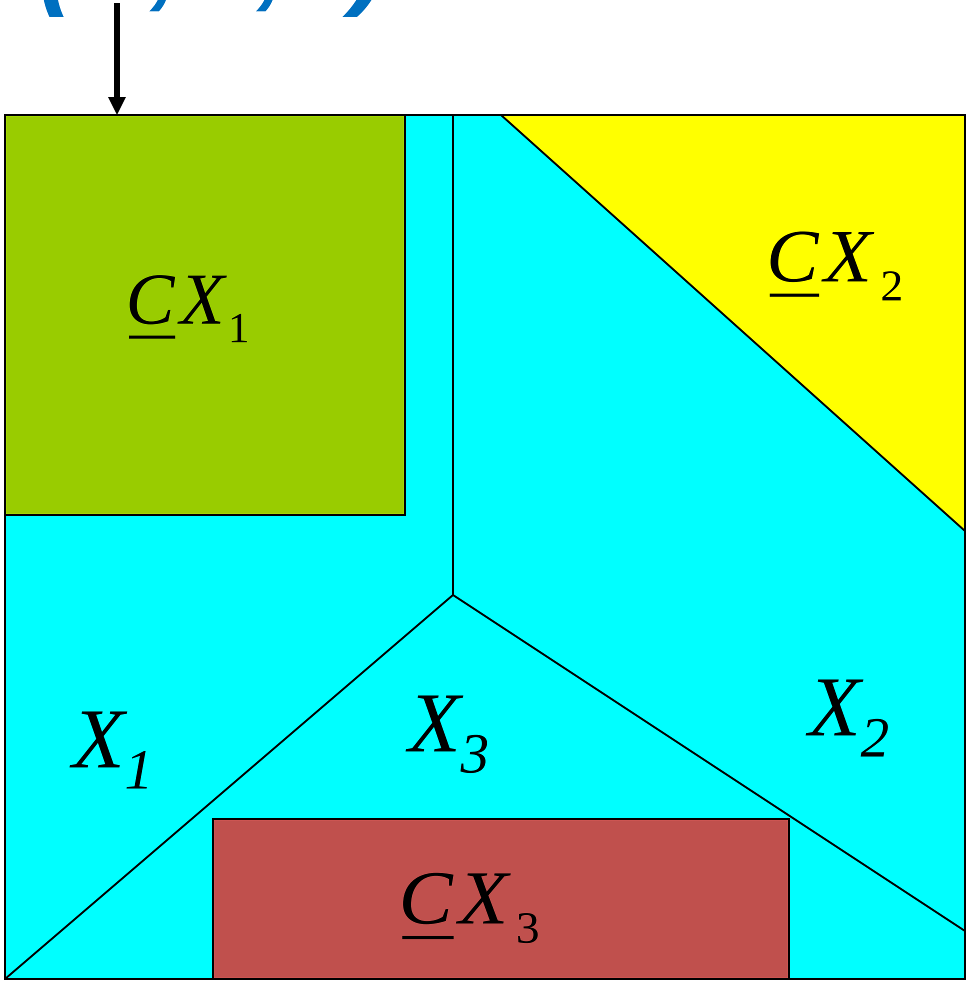
Remark: Analogously one can define *C*-positive region of *D* if we have a set *D* of decisions instead of one decision.

POSITIVE REGION OF DECISION SYSTEM

$T=(U,A,d)$

Decision classes:

$U/d=\{X_1,X_2,X_3\}$

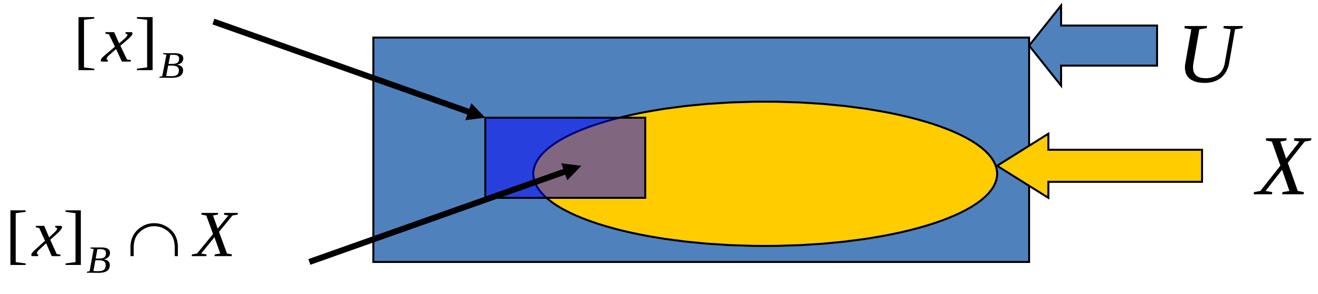


ROUGH MEMBERSHIP

- The rough membership function quantifies the degree of relative overlap between the set *X* and the equivalence class $[x]_B$ to which *x* belongs.

$$\mu_X^B : U \rightarrow [0,1] \qquad \mu_X^B(x) = \frac{|[x]_B \cap X|}{|[x]_B|}$$

- The rough membership function can be interpreted as a frequency-based estimate of $P(x \in X \mid u)$, where $u=[x]_B$ is the equivalence relation of *IND(B)*.



DEPENDENCY OF ATTRIBUTES

Let *D* and *C* be subsets of *A*. *D* depends on *C* in a degree *k* $(0 \leq k \leq 1)$,

$$C \Rightarrow_k D,$$

where $k = \gamma(C, D) = \frac{|POS_C(D)|}{|U|}$

DESCISION RULES

$$T = (U, A, d) - \text{decision system}$$

Decision rule

$$a_{i_1} = v_{i_1} \wedge \ldots \wedge a_{i_k} = v_{i_k} \Rightarrow d = v \in V_d$$

Generalized decision rule

$$a_{i_1} = v_{i_1} \wedge \ldots \wedge a_{i_k} = v_{i_k} \Rightarrow \partial_A = V \subseteq V_d$$

MINIMAL SETS OF CONDITION ATTRIBUTES PRESERVING DISCERNIBILITY CONSTRAINTS: REDUCTS

- between discernible objects in a given information system ➔ **reducts in information systems**
- between objects from different decision classes ➔ **decision reducts**
- between a given object x with a decision *i* and other objects with a decision different from *i* ➔ **local reducts relative to the object** x
- ...

REDUCTS IN INFORMATION SYSTEMS

- For a given information system $IS=(U, A)$ we are searching for minimal subsets $B \subseteq A$ such that

$$IND_{IS}(B) = IND_{IS}(A)$$

- *RED(IS)* or *RED(A)* – the set of all reducts in *IS*.
- $CORE(IS)=\bigcap RED(IS)$.

PROBLEMS WITH REDUCTS

- The number of reducts can be large, e.g., in case if reducts of information systems some information systems can have exponential number of reducts with respect to the number of attributes
- Problems of computing minimal reducts are of high complexity, usually they are NP-hard.

Fortunately there have been developed efficient heuristics for computing relevant reducts or sets of reducts based on

BOOLEAN REASONING.

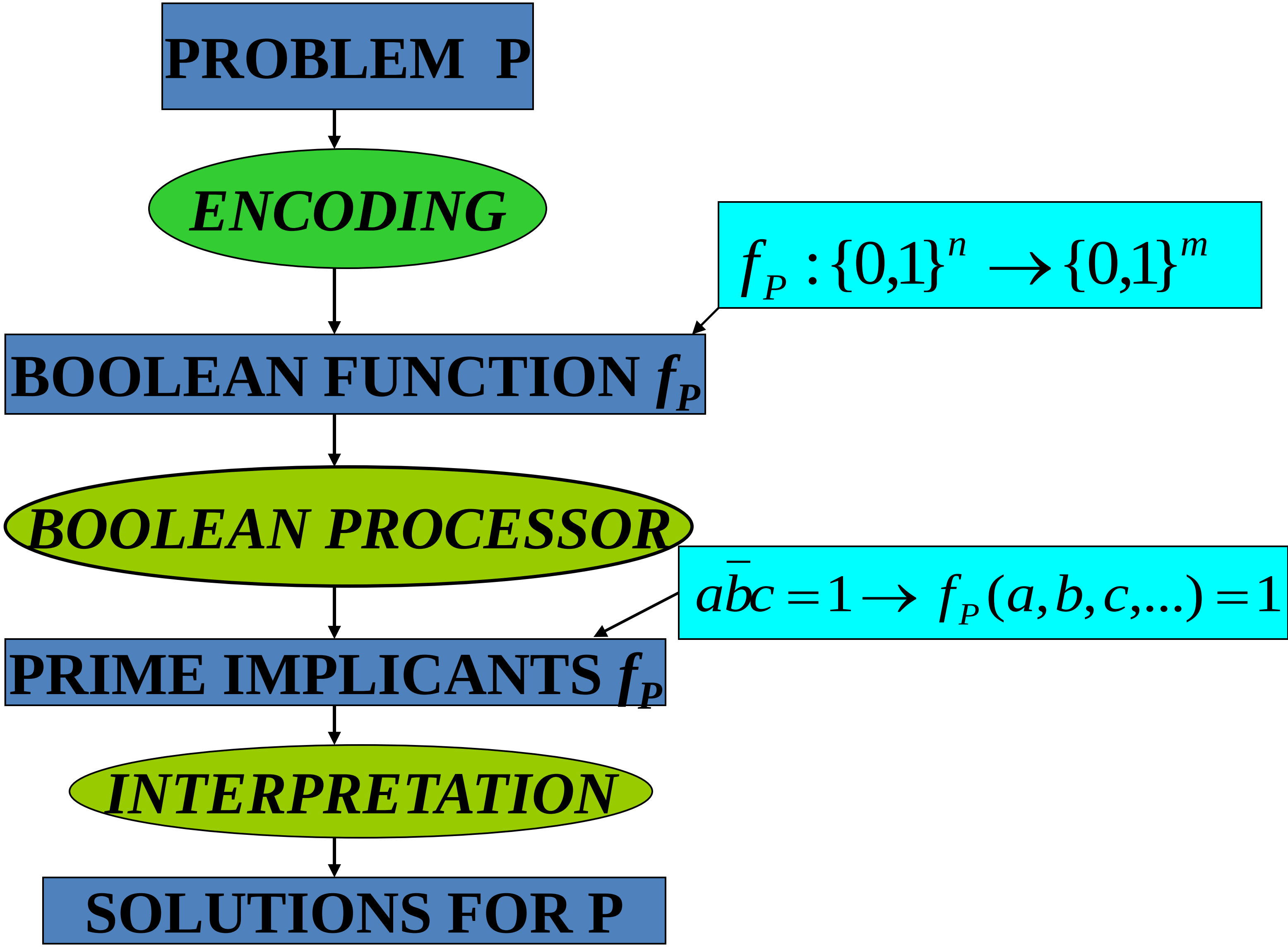
RELATIONSHIPS WITH OTHER APPROACHES

- Fuzzy sets
- Dempster-Shafer Theory
- **Boolean Reasoning**
- Statistics
- Mereology
- Mathematical Morphology
- ...

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

BOOLEAN REASONING FOR COMPUTING REDUCTS IN INFORMATION SYSTEMS

REDUCTS IN *IS*

$$IS = (U, A)$$

↓

$$Discernibility \ \ matrix$$

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

↓

$$Discernibility \ \ function$$

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

↓

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

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

REDUCTS IN *IS*

		x_i	
	…		…
x_j		a, b, c	
	…	c, e	…

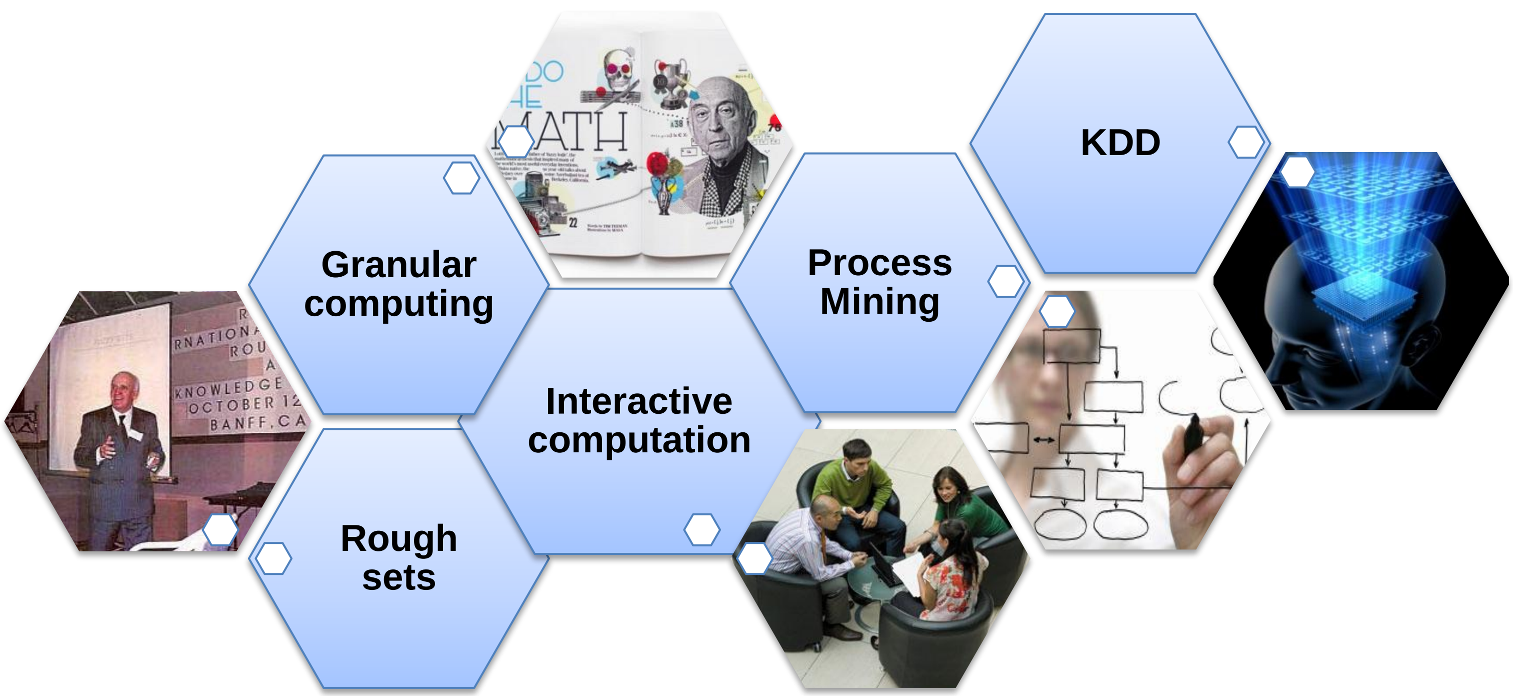
$$(a \vee b \vee c) \wedge (c \vee e) \wedge \ldots$$

$$\Downarrow$$

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

CHALLENGES

for making progress in constructing of the high quality intelligent systems



AGENDA

- MOTIVATION
- INTERACTIVE ROUGH GRANULAR COMPUTING
  - CONTRUCTION OF GRANULES
    - HIERARCHICAL LEARNING AND ONTOLOGY APPROXIMATION
      - ROLE OF DOMAIN KNOWLEDGE
      - CASE STUDIES
  - INTERACTIVE COMPUTATIONS AND DECISION SUPPORT IN PROBLEM SOLVING
    - CONTROL
      - ADAPPTIVE JUDGMENT
        - REASONING ABOUT CHANGES – ROUGH CALCULUS
      - BEYOND ONTOLOGIES: EVOLVING COMMUNICATION LANGUAGES
      - RISK MANAGEMENT IN INTERACTIVE COMPUTATIONAL SYSTEMS
        - CASE STUDY: ALGORITHMIC TRADING
  - CHALLENGES

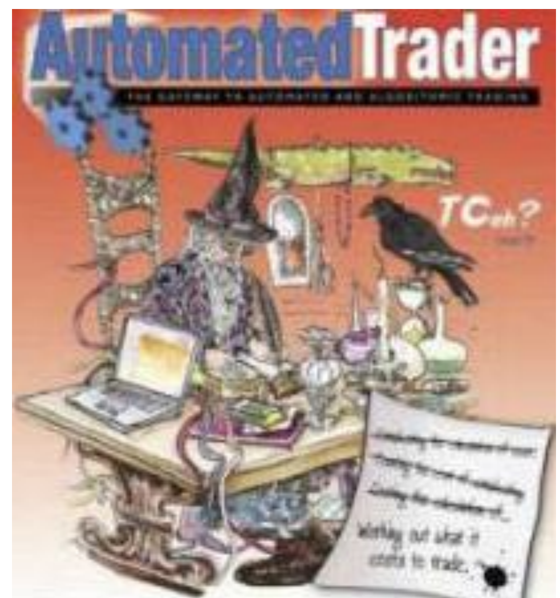
MOTIVATION

- Making progress in constructing of the high quality intelligent systems
- Examples: approximation of complex vague concepts such as guards of actions or behavioral patterns
- Reasoning about vague concepts

OBSTACLE AVOIDANCE

UAV

ROBO-CUP



REAL-LIFE PROJECTS

UAV control of unmaned helicopter (Wallenberg Foundation, Linkoeping University)

Medical decision support (glaucoma attacs, respiratory failure,…)

Fraud detection (Bank of America)

Logistics (Ford GM)

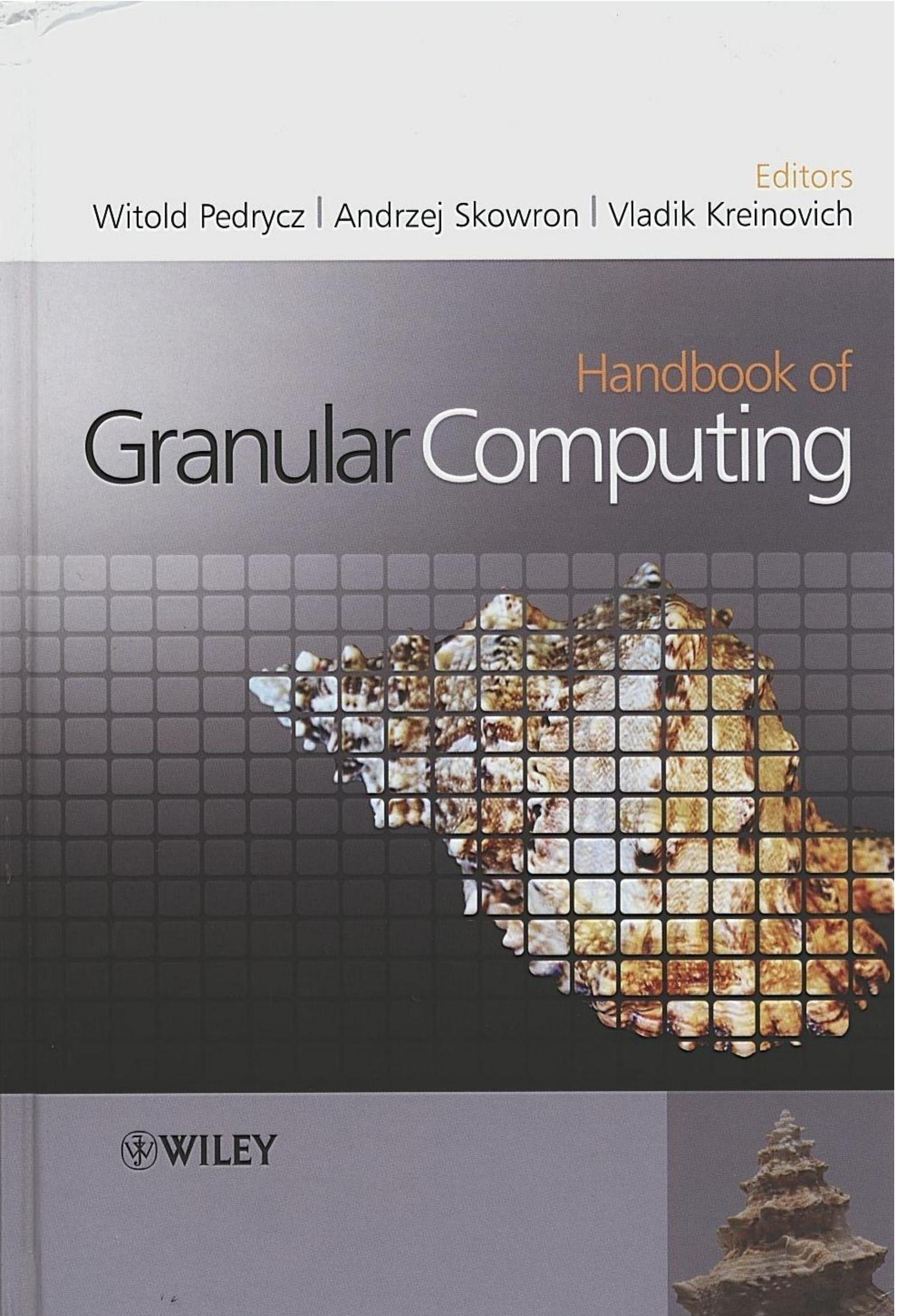
Dialog Based Search Engine (UNCC, Excavio)

Algorithmic trading (Adgam)

Semantic Search (SYNAT) (NCBiR)

Firefighter Safty (NCBiR)

…



Plays a key role in implementation of the strategy of divide-and-conquer in human problem-solving – Lotfi 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

LESLIE VALIANT: TURING AWARD 2010

March 10, 2011:

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

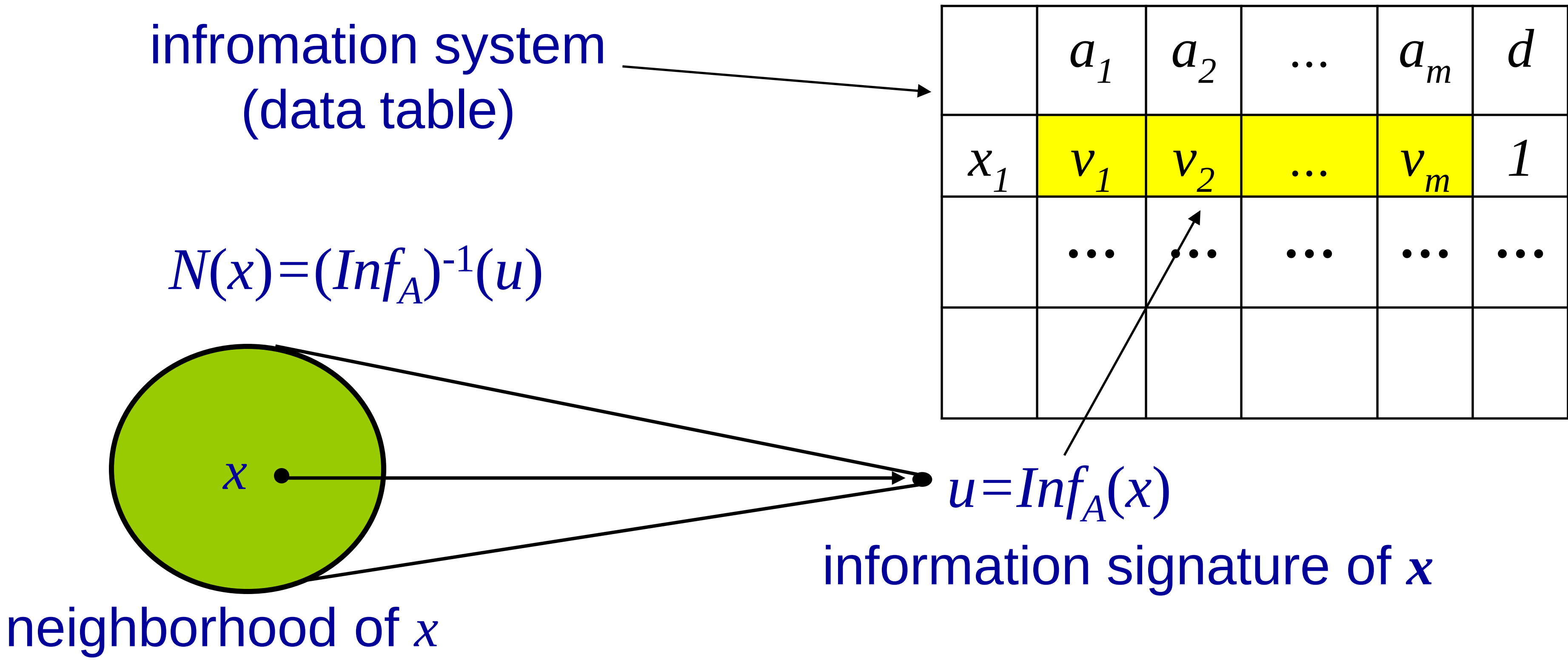
Current research of Professor Valiant

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.

INFORMATION GRANULES

INDISCERNIBILITY GRANULES

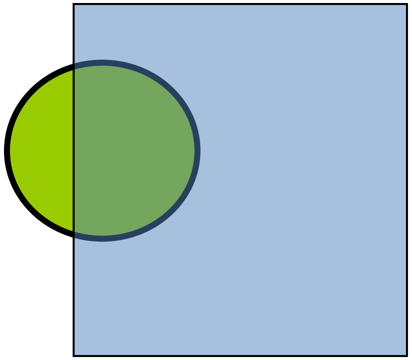


τ

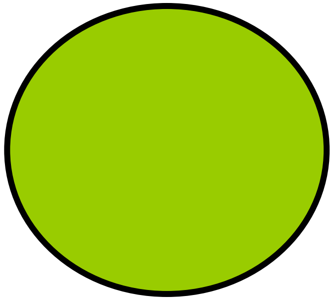
$$xIND(A)y \;\; iff \;\; Inf_A(x) = Inf_A(y)$$

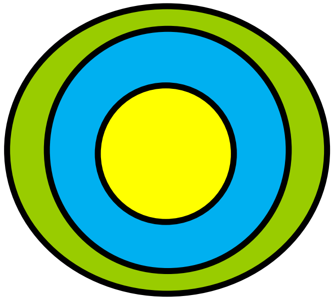
τ

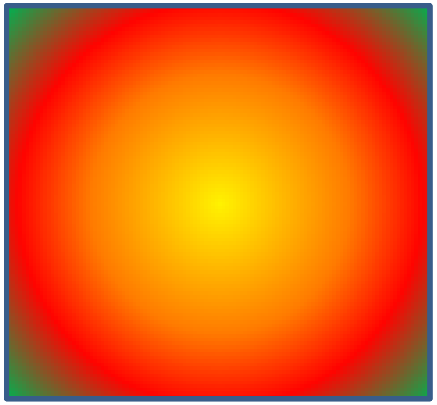
tolerance or similarity

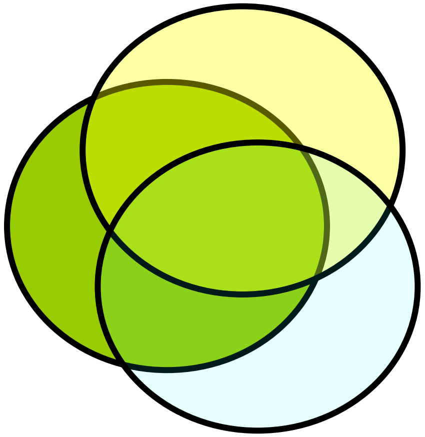


ELEMENTARY GRANULES
+
INTERACTIVE
CALCULULI OF GRANULES



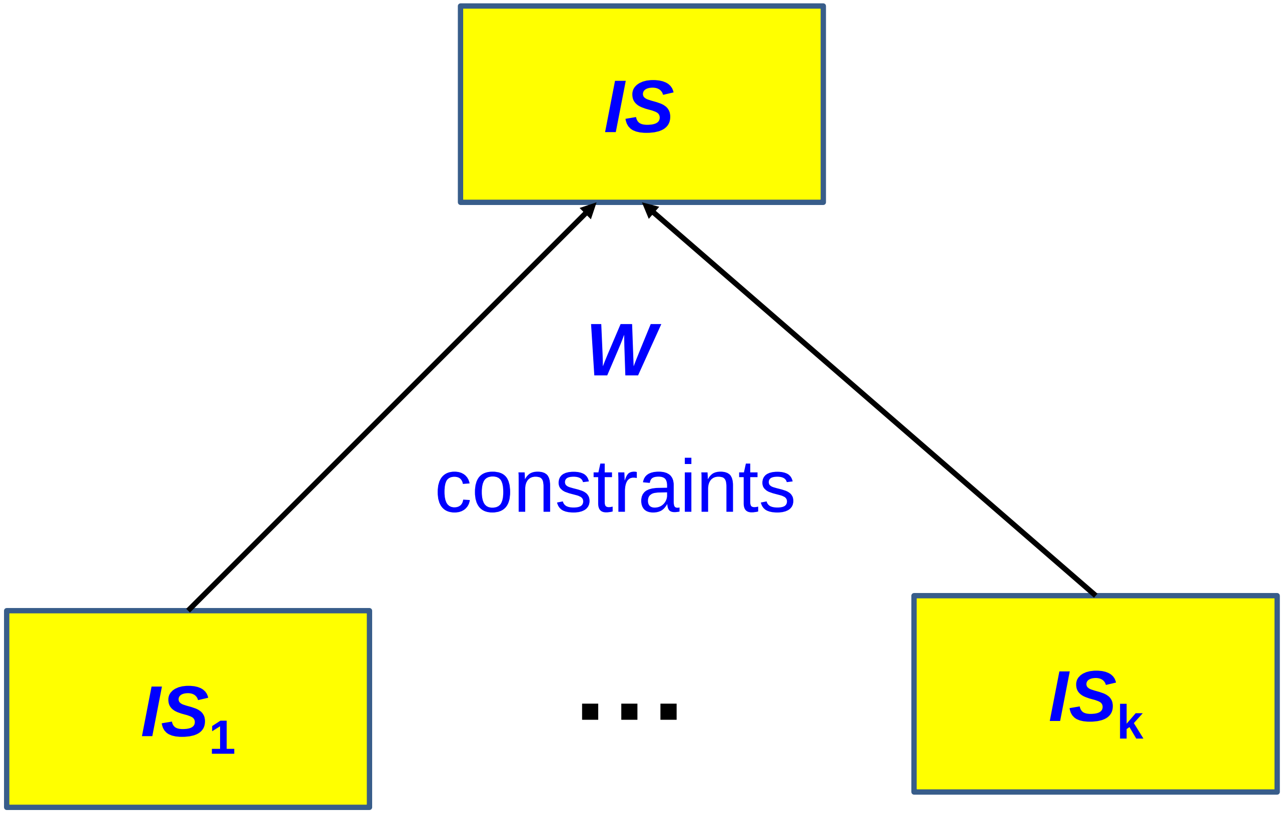






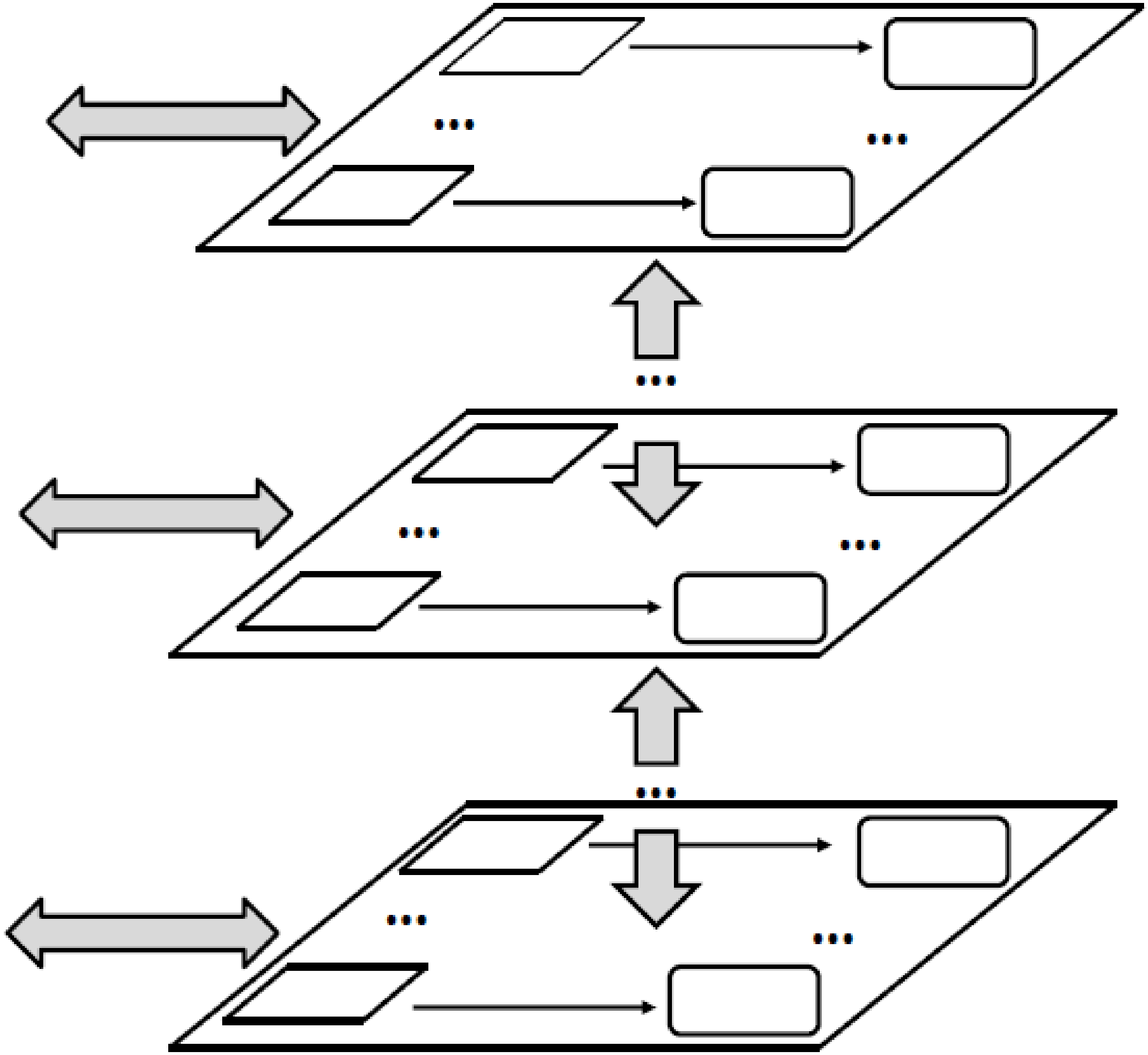
...

JOIN WITH CONSTRAINTS



Objects (granules) in *IS* are composed out of attribute value vectors from $IS_1 \ldots IS_k$ satisfying *W*

INTERACTIVE HIERARCHICAL STRUCTURES

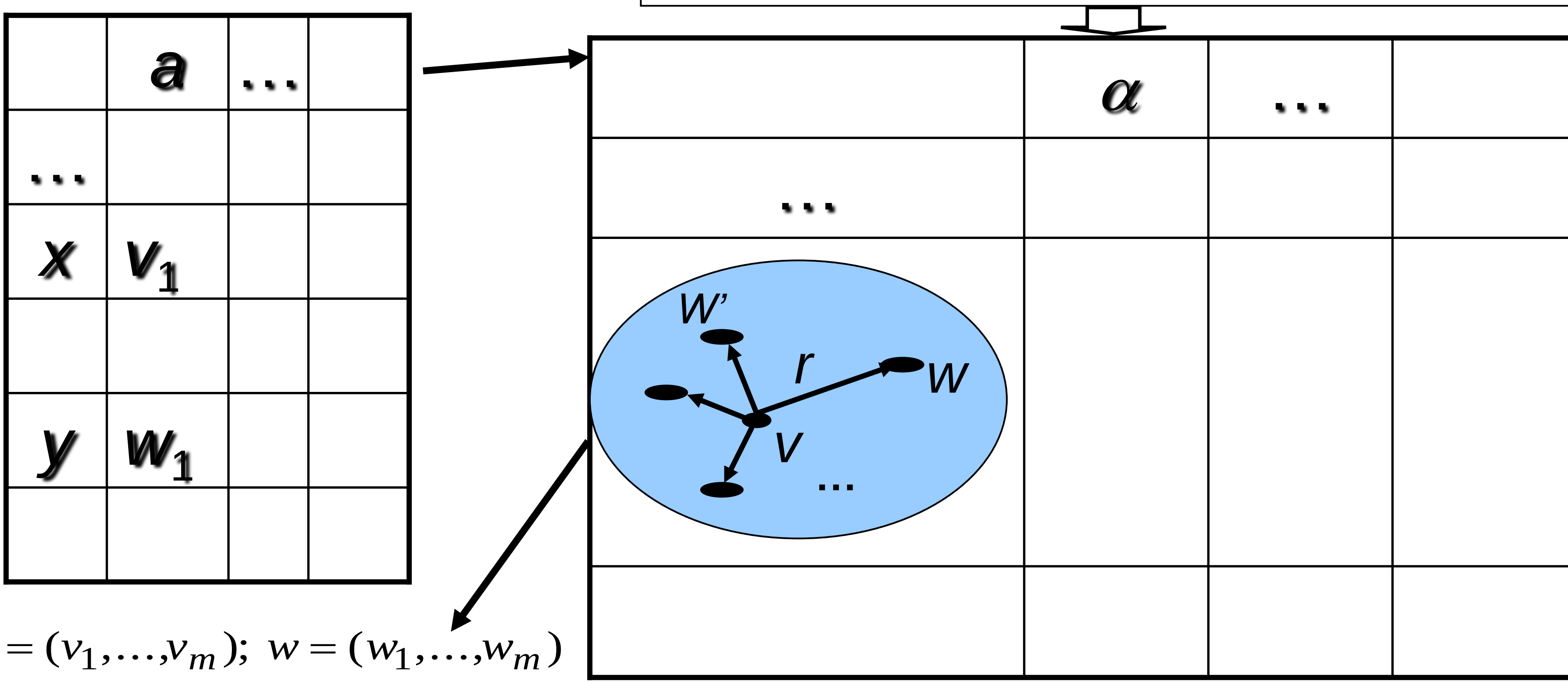


STRUCTURAL OBJECTS

SEARCHING FOR RELEVANT FEATURES

GENERALIZATIONS OF GRANULES: TOLERANCE GRANULES

invariants over tolerance classes; compare invariants in the Gibson approach



$$v = (v_1,\ldots,v_m);\ w = (w_1,\ldots,w_m)$$

$$v\,r\,w \ iff \ v_i r_i w_i \ for\ i = 1,..m$$

$$r(v) = \{w : v\,r\,w\}$$

$$\|r(v)\| = \bigcup\{\|w\| : w \in r(v)\}$$

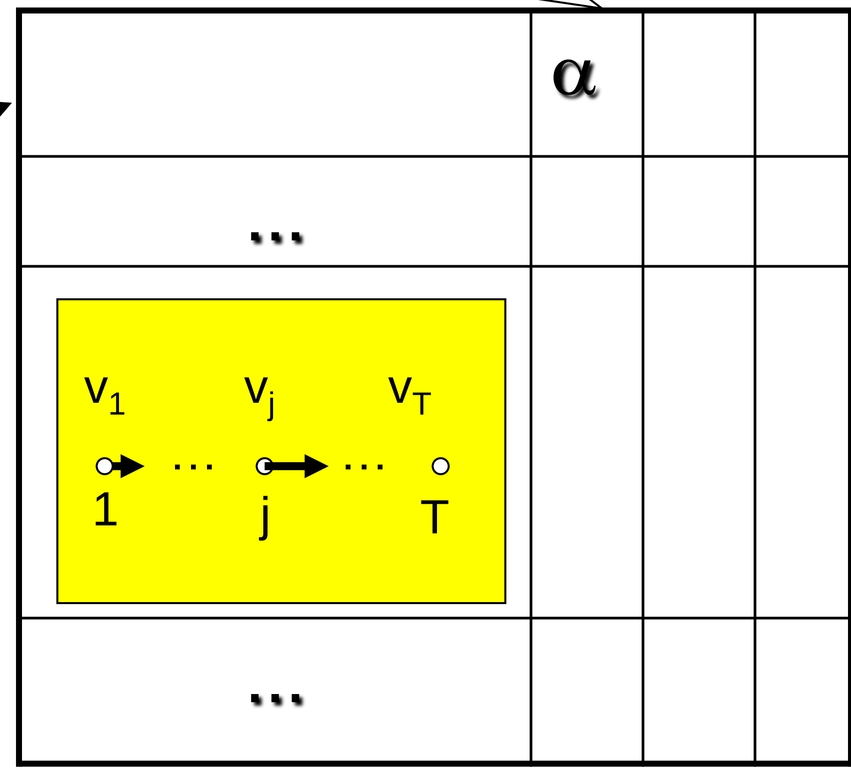
GENERALIZATION from *v* to *r*(*v*)

GRANULES REPRESENTING STRUCTURES OF OBJECTS

properties of time windows

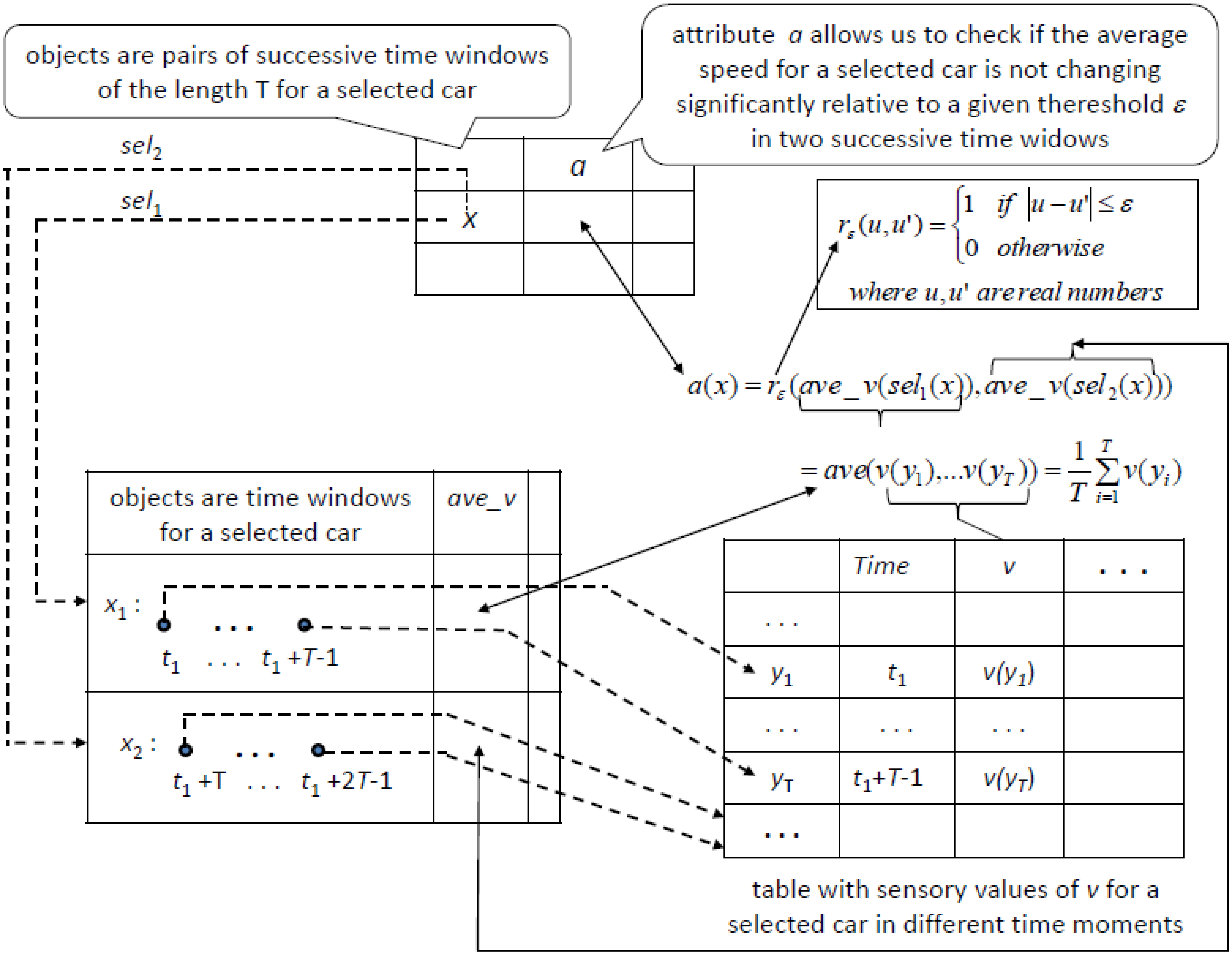
TIME WINDOWS

	t	t_T	a_1	…
…	…	…		
x	i	mod(i,T)	$V_{1,i}$	…
…	…			

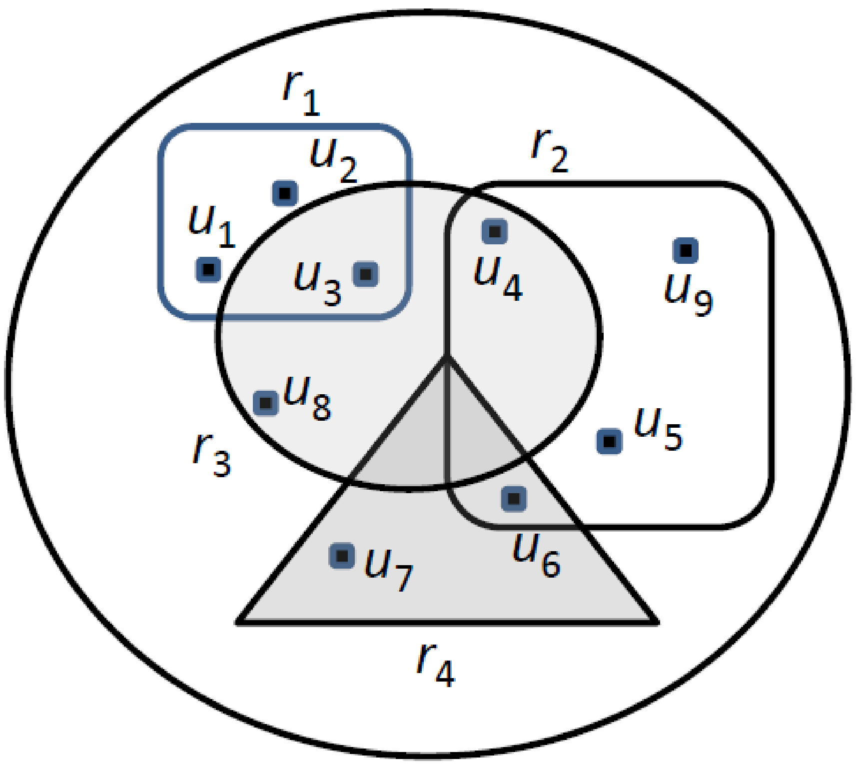


$V_i=(v_{1,i},\ldots,v_{m,i})$

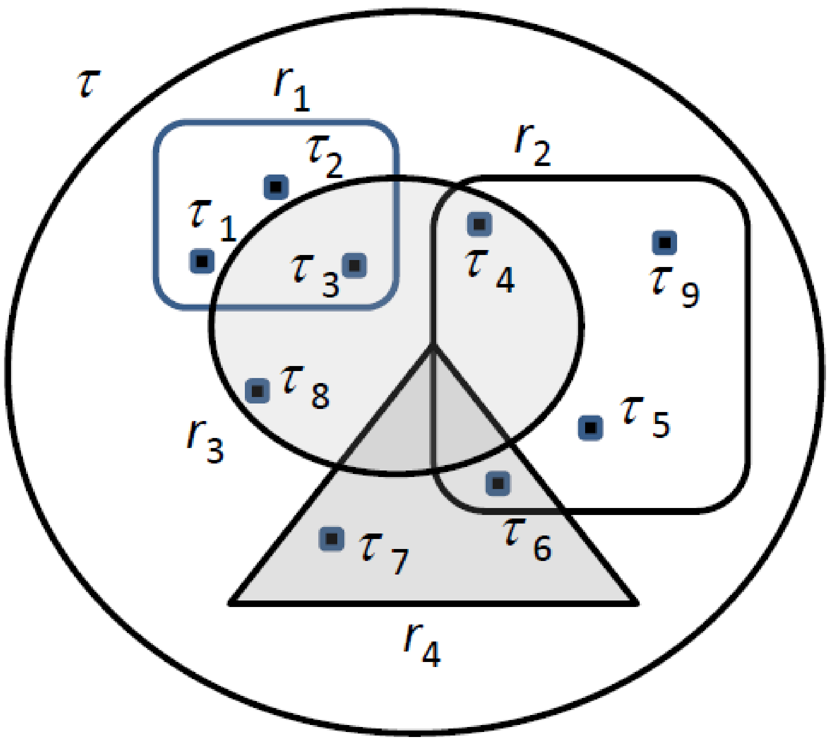
COMPLEX ATTRIBUTES



STRUCTURAL GRANULES SEARCHING FOR RELEVANT FEATURES



object



object of type τ

DEFINABLE GRANULES

ROUGH GRANULES

APPROXIMATION OF GRANULES

INTERACTIONS

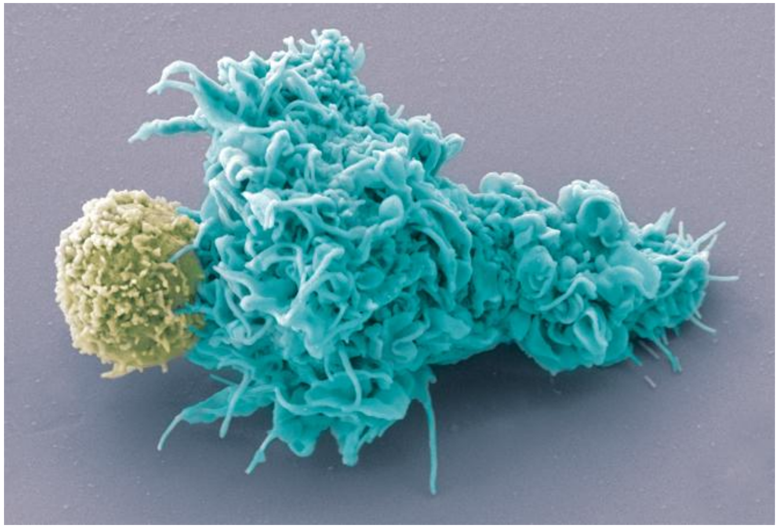
INTERACTIONS

[…] **interaction** is a critical issue in the understanding of complex systems of any sorts: as such, it has emerged in several well-established scientific areas other than computer science, like biology, physics, social and organizational sciences.

Andrea Omicini, Alessandro Ricci, and Mirko Viroli, The Multidisciplinary Patterns of Interaction from Sciences to Computer Science. In: D. Goldin, S. Smolka, P. Wagner (eds.): Interactive computation: The new paradigm, Springer 2006

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.



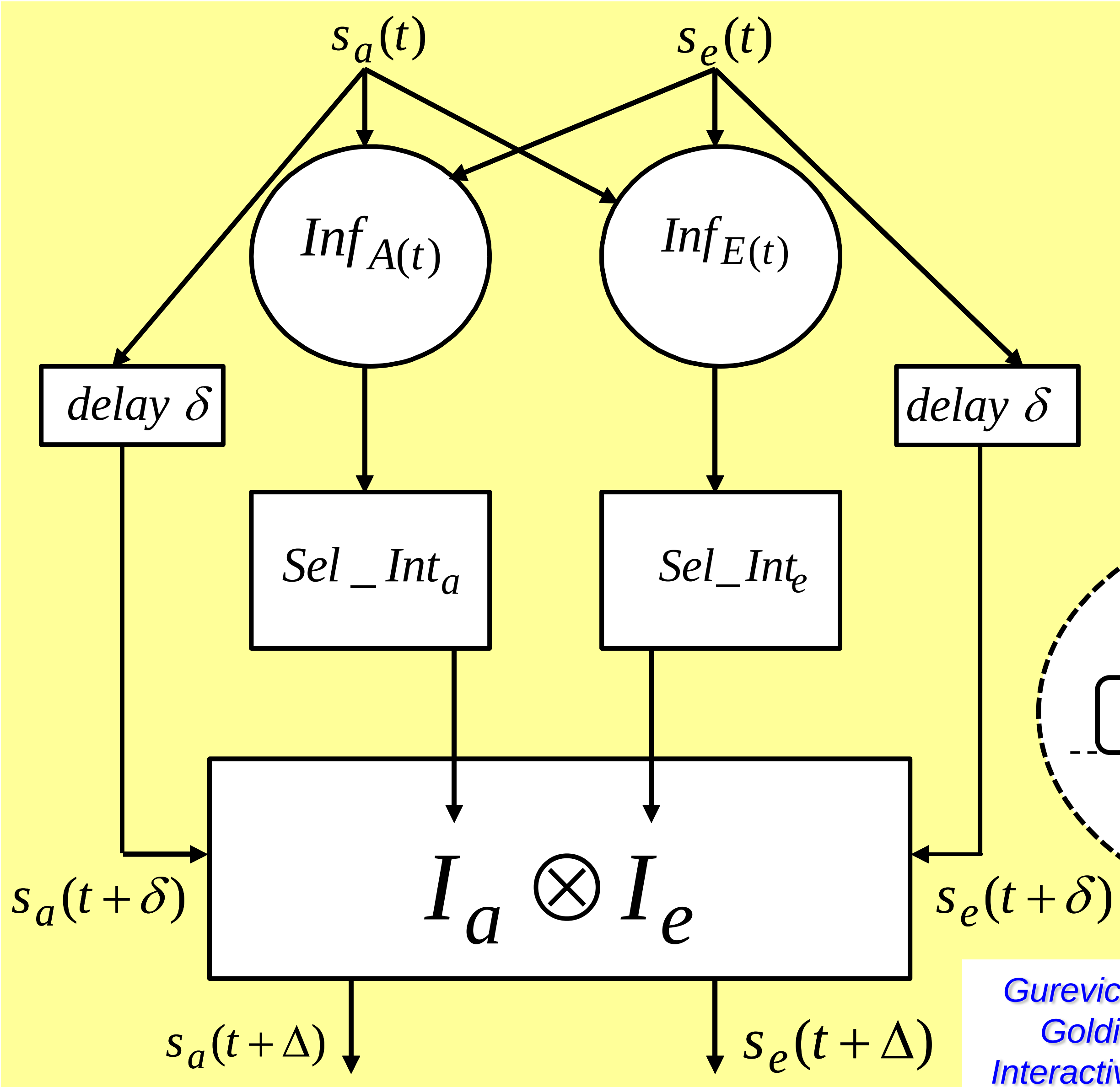
A human dendritic cell (blue pseudo-color) in close interaction with a lymphocyte (yellow pseudo-color). This contact may lead to the creation of an immunological synapse.

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

http://www.cell.com/Cell_Picture_Show

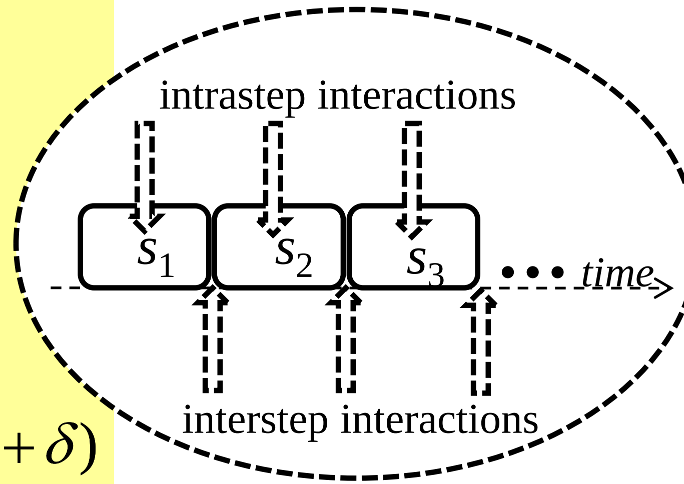
Andrzej Ehrenfeucht, Grzegorz Rozenberg: Reaction Systems: A Model of Computation Inspired by Biochemistry, LNCS 6224, 1–3, 2010

GENERAL SCHEME OF INTERACTION



TRANSITION RELATION

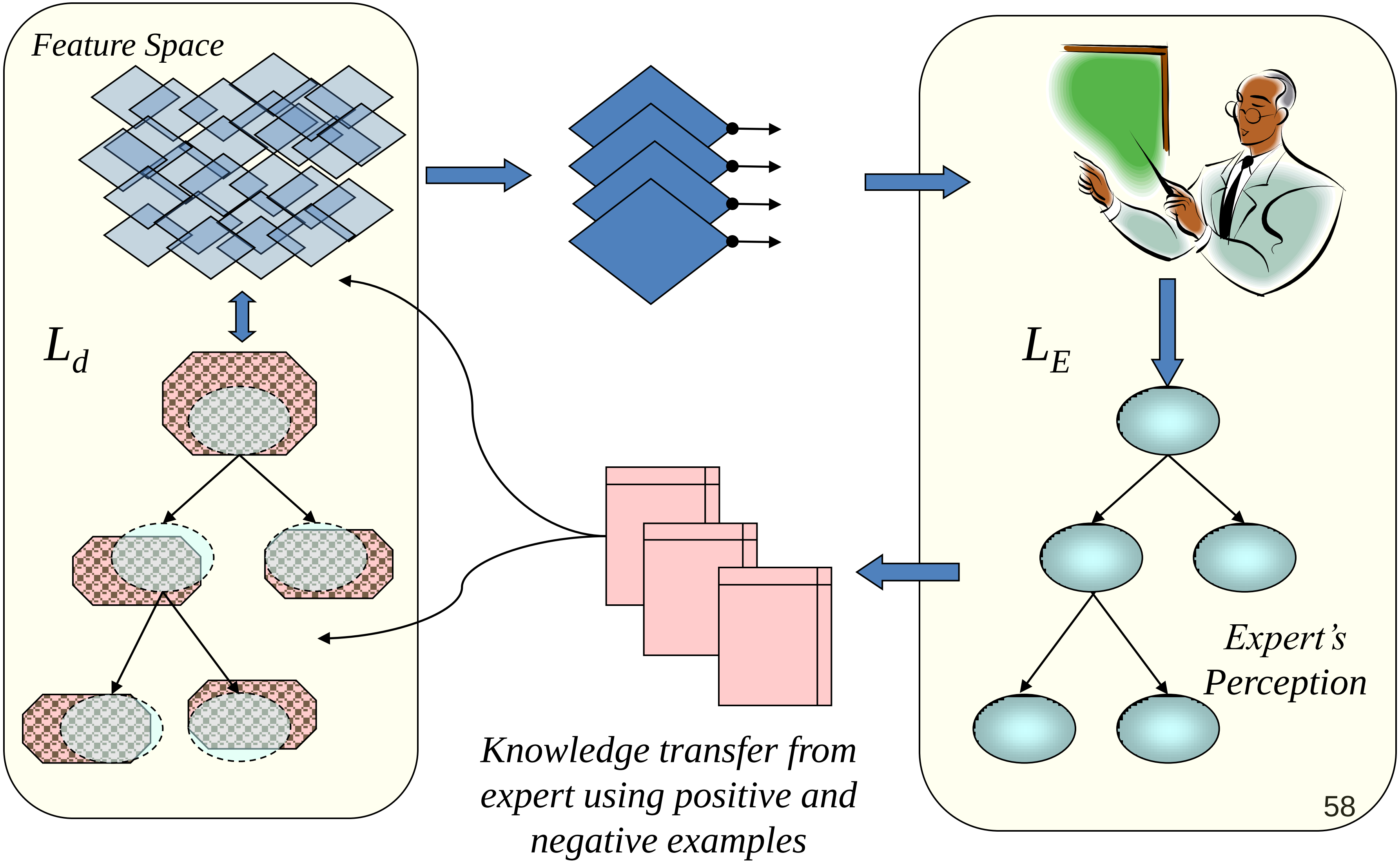
$$(s_a(t), s_e(t)) \rightarrow s_a(t+\Delta), s_e(t+\Delta)$$



Gurevich, Y.: Interactive Algorithms . In: D. Goldin, S. Smolka, P. Wagner (eds.): Interactive computation: The new paradigm, Springer 2006

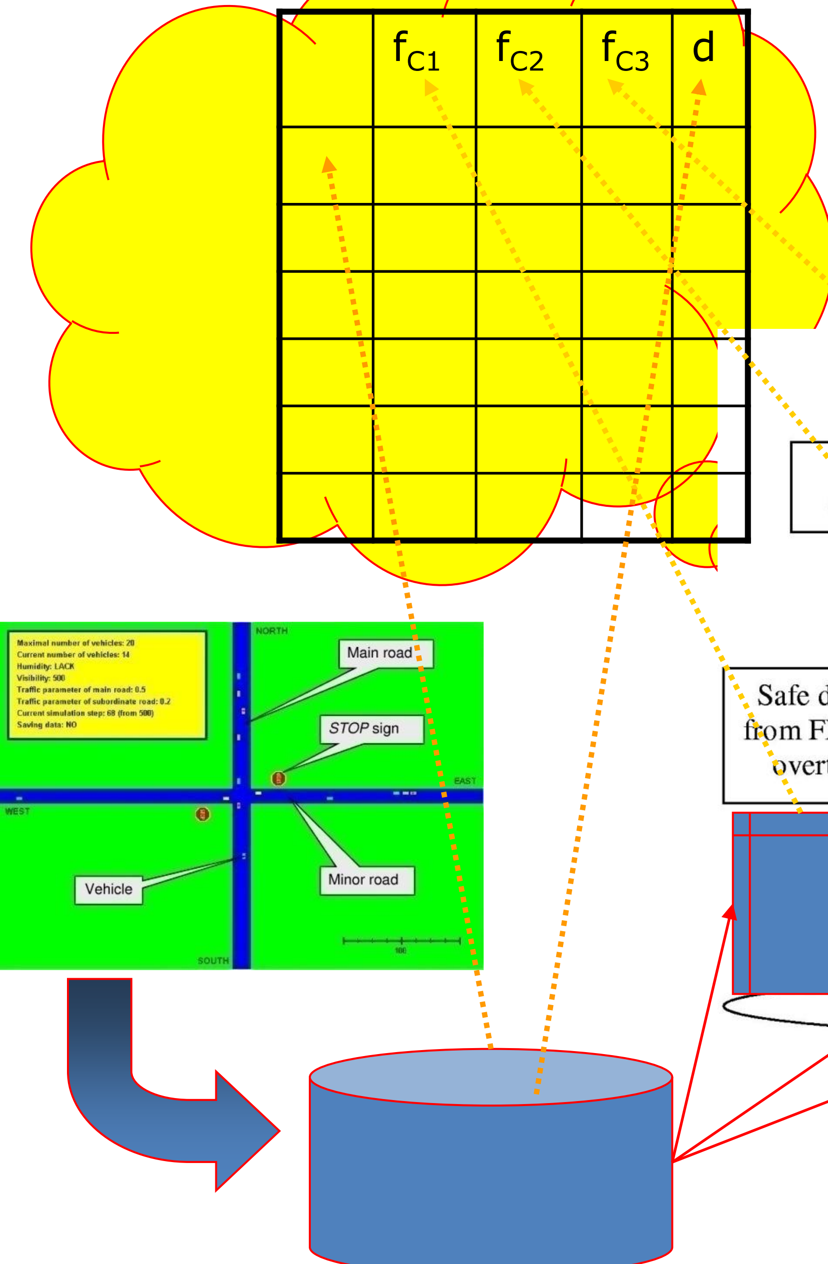
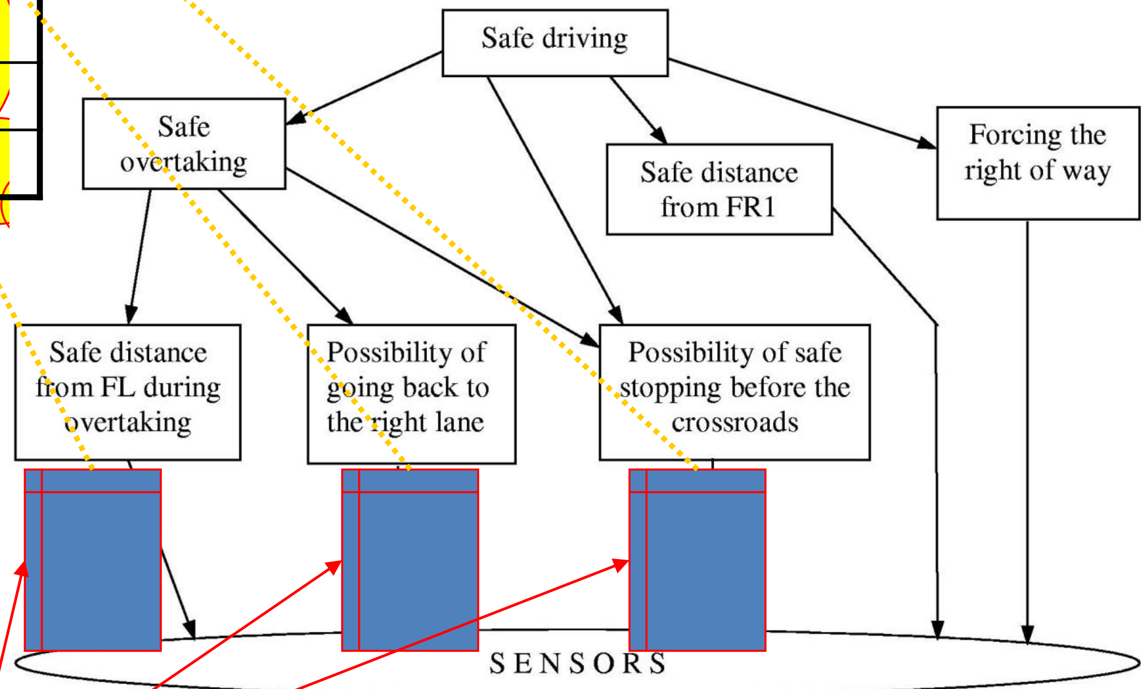
HIERARCHICAL LEARNING IN INTERACTION WITH DOMAIN EXPERTS

ROUGH SET BASED ONTOLOGY APPROXIMATION



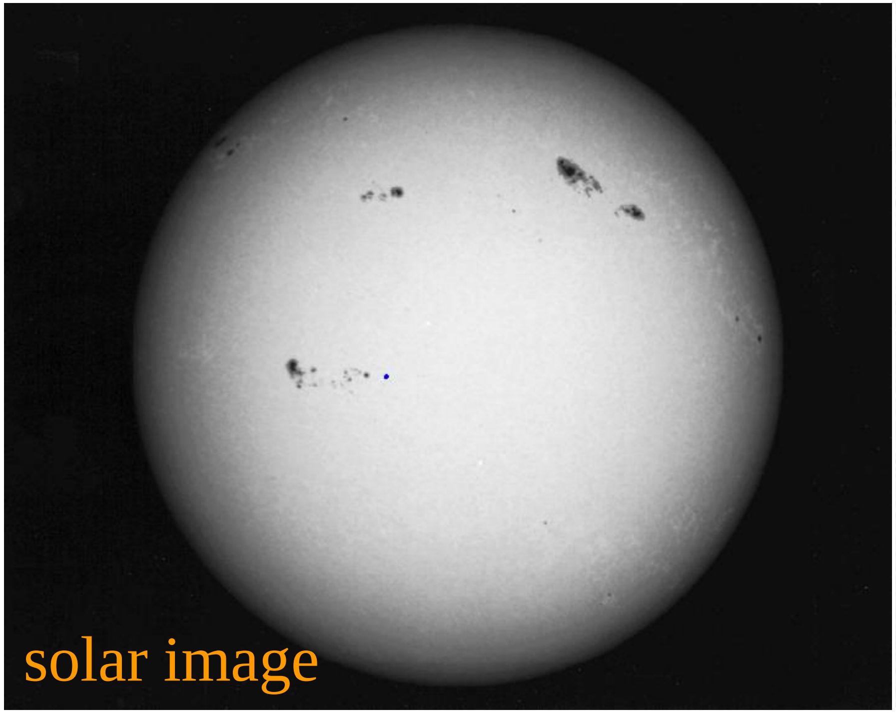
UAV

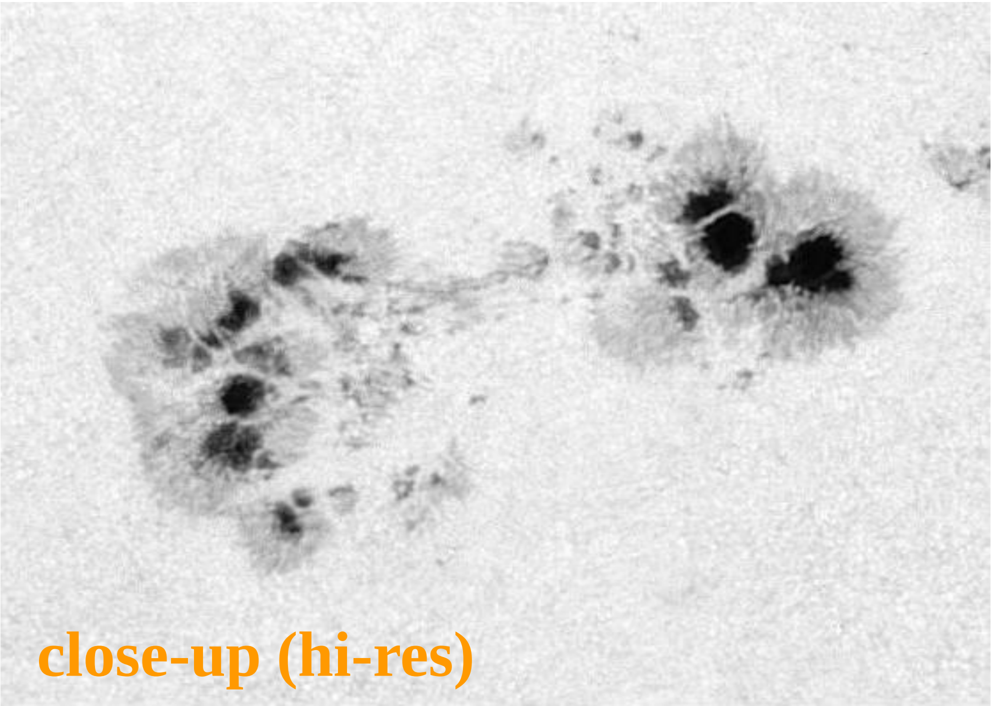
COMPLEX CONCEPT APPROXIMATION

J. Bazan, S.H. Nguyen. H.S. Nguyen, A. Skowron (RSCTC 2004)

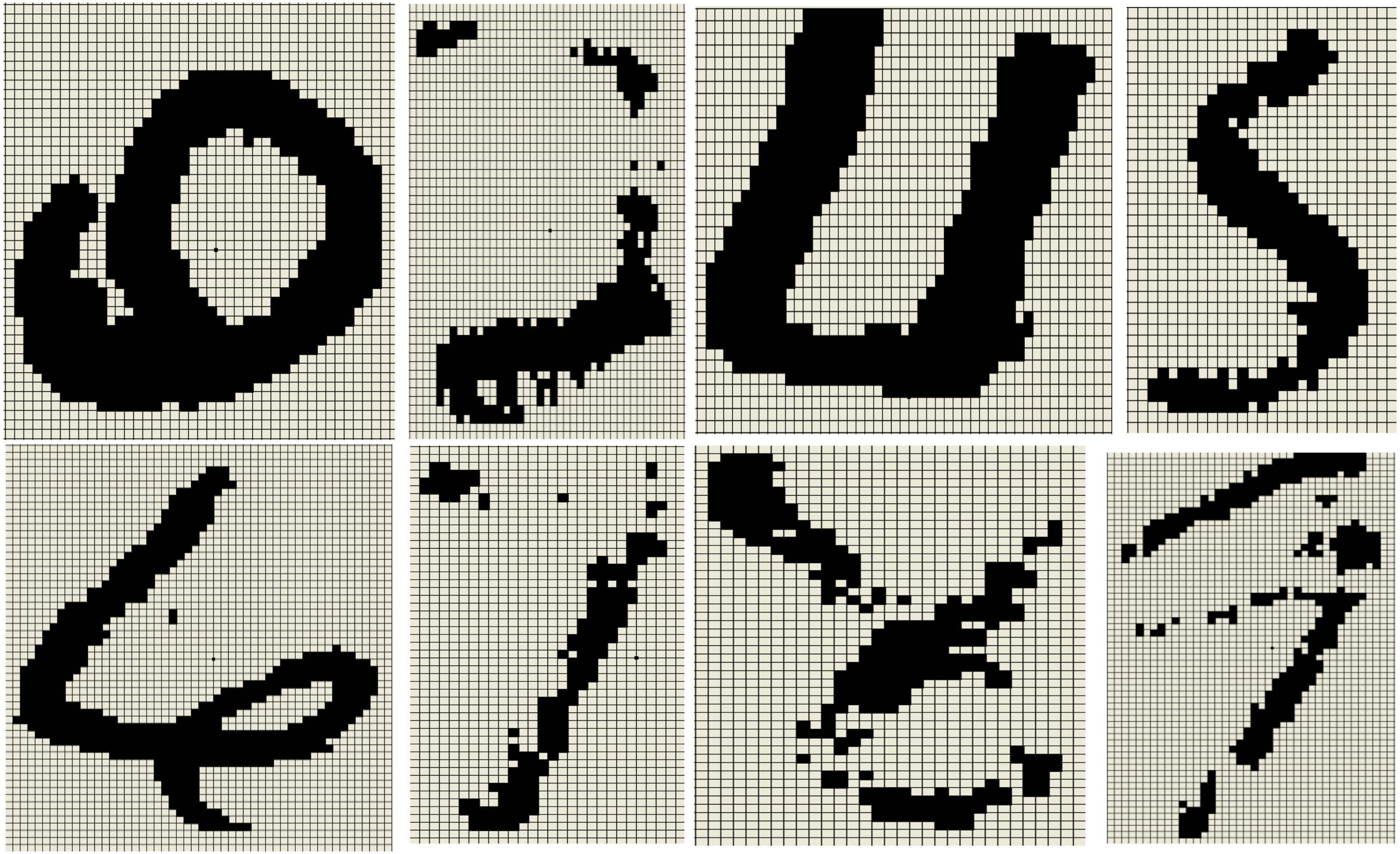
SUNSPOT CLASSIFICATION





T.T. Nguyen, C.P. Willis, D.J. Paddon, S.H. Nguyen, H.S. Nguyen: Learning Sunspot Classification. Fundamenta Informaticae 72(1-3): 295-309 (2006)

HARD SAMPLES

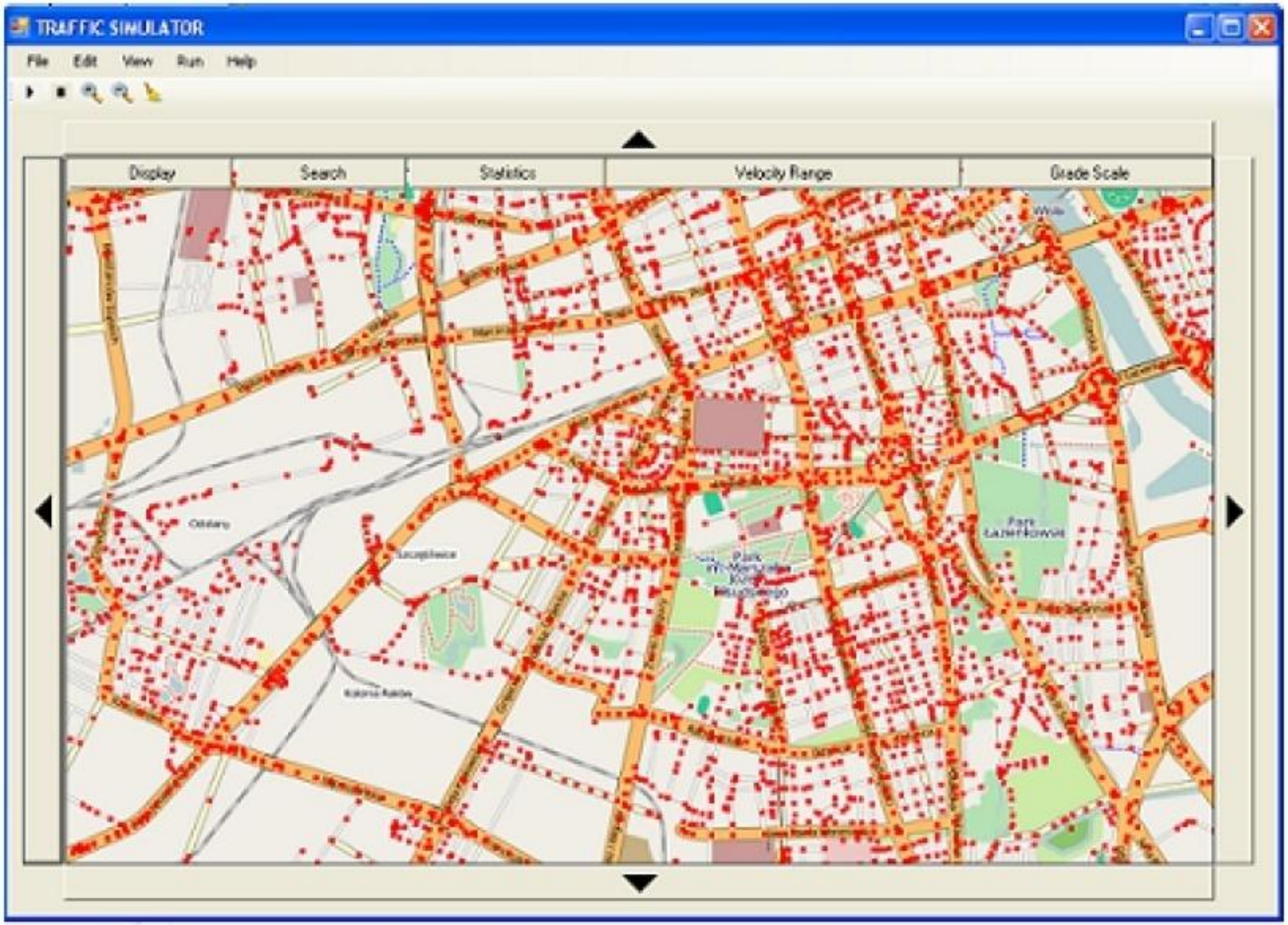


Nguyen, T.T., Skowron, A.: Rough-granular computing in human-centric information processing. In; Bargiela, A., Pedrycz, W. (eds.), Human-Centric Information Processing Through Granular Modelling, Springer, Heidelberg (2009) 1-30

MEDICAL DIAGNOSIS AND THERAPY SUPPORT
RESPIRATORY FAILURE

Jan Bazan et al, Cooperation with Polish-American Pediatric Institute,
Jagiellonian University Medical College, Cracow, Poland

SCALABILITY



ADAPTIVE JUDGMENT

LESLIE VALIANT: TURING AWARD 2010

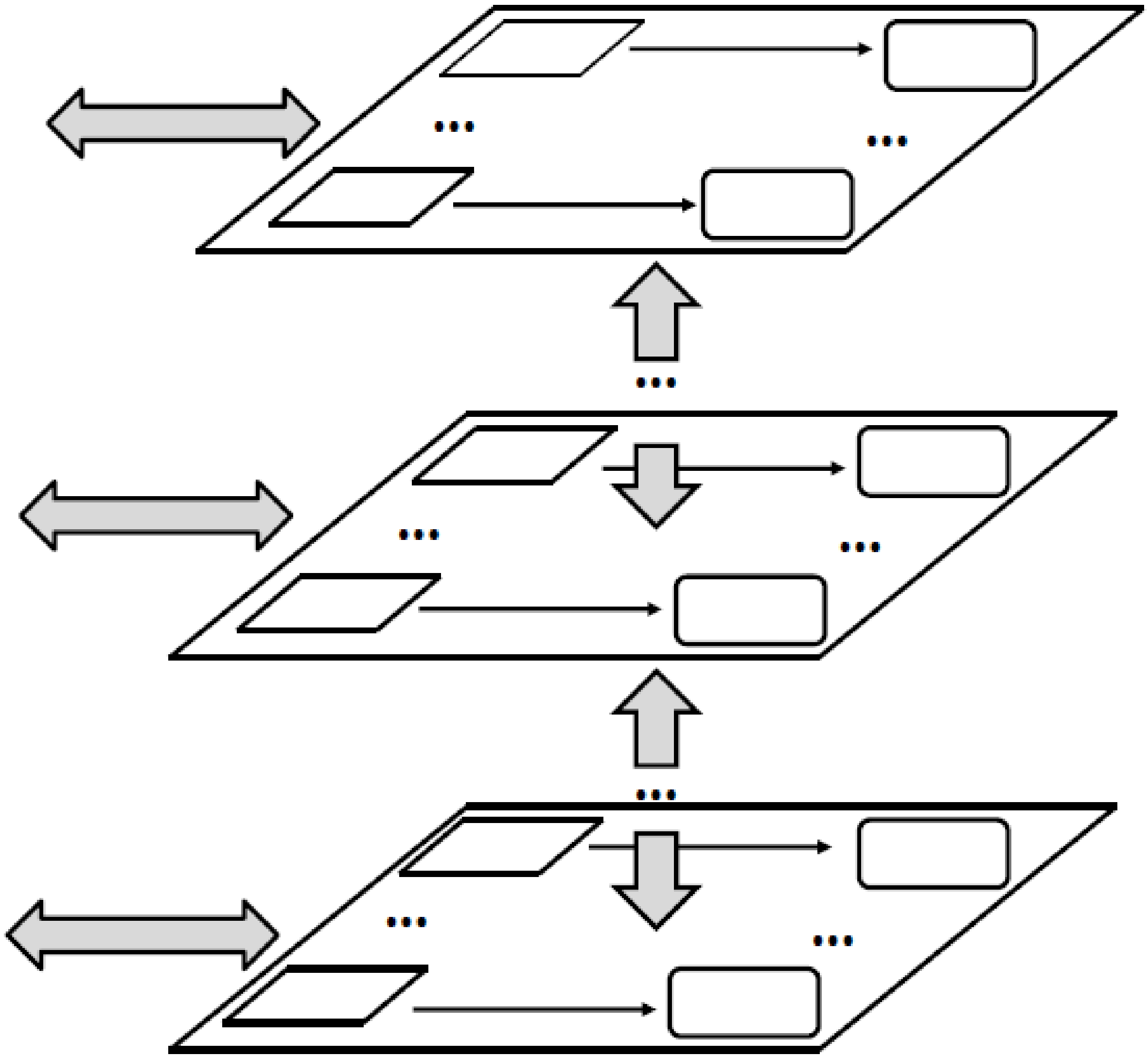
.

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.

INTERACTIVE HIERARCHICAL STRUCTURES



ADAPTIVE JUDGMENT

- Searching for relevant approximation spaces
  - new features, feature selection
  - rule induction
  - measures of inclusion
  - strategies for conflict resolution
  - …
- Adaptation of measures based on the minimal description length: quality of approximation vs description length
- Reasoning about changes
- Perception (action and sensory) attributes selection
- Adaptation of quality measures over computations relative to agents
- Adaptation of object structures
- Strategies for knowledge representation and interaction with knowledge bases
- Ontology acquisition and approximation
- Language for cooperation development and evolution
- …

REASONING ABOUT CHANGES

ROUGH CALCULUS

PROCESS MODELS AND INTERACTIONS

Example

$$x_i(t+1) = f(x_i(t)) + \kappa \frac{1}{d_i} \sum_{j;\, j \approx i} \left(f(x_j(t-\tau)) - f(x_i(t)) \right)$$

neighborhood relation

$$\dot{x}_i(t) = f(x_i(t)) + \varepsilon\kappa \frac{1}{d_i} \sum_{j;\, j \approx i} \left(f(x_j(t-\tau)) - f(x_i(t)) \right)$$

Feng, J., Jost, J., Minping, Q. (eds): Network: From Biology to Theory, Springer, Berlin, 2007

?

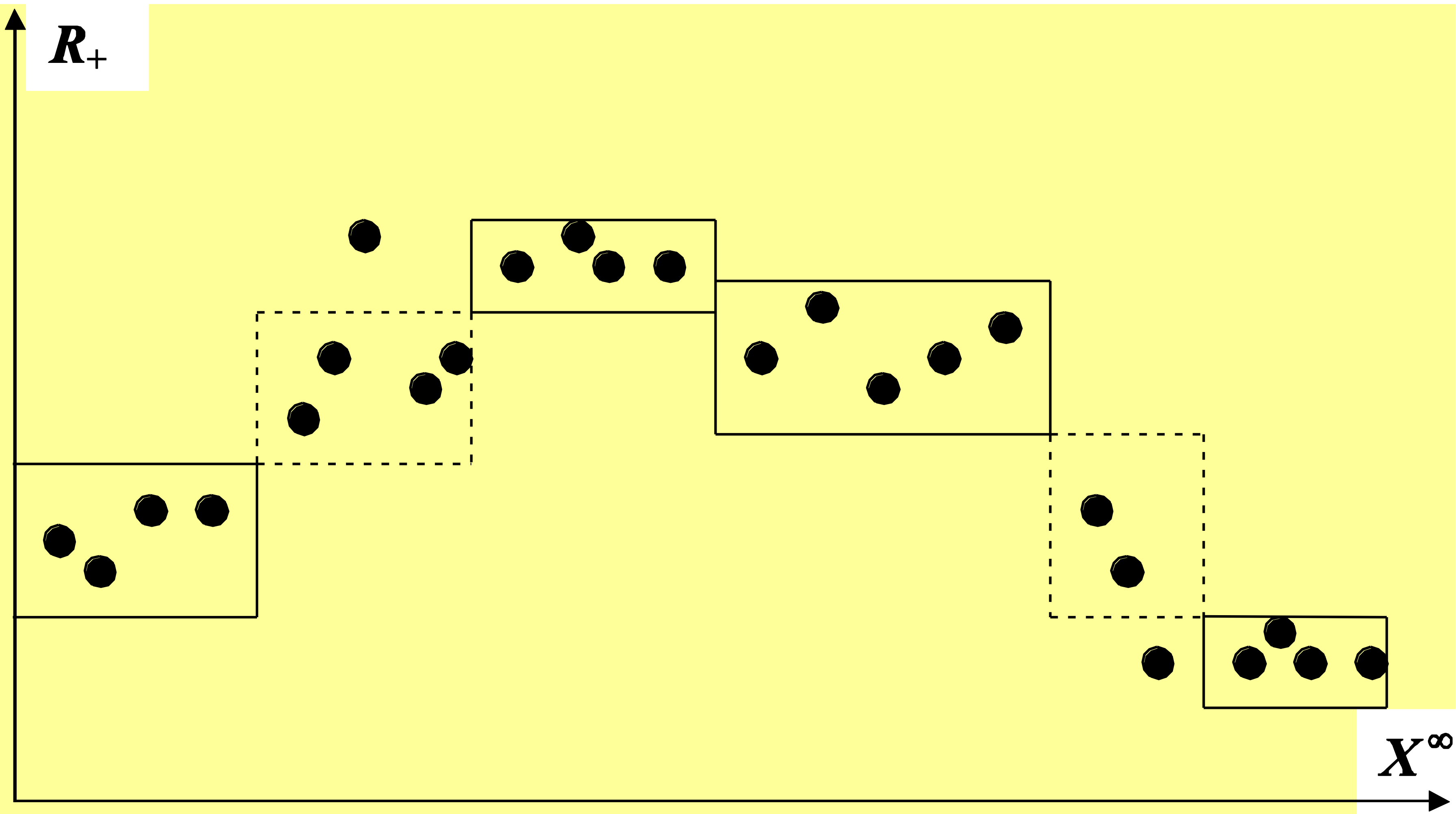
$$\frac{ds}{dt} = G(t, s(t), e(t))$$

$$\frac{de}{dt} = H(t, s(t), e(t))$$

?

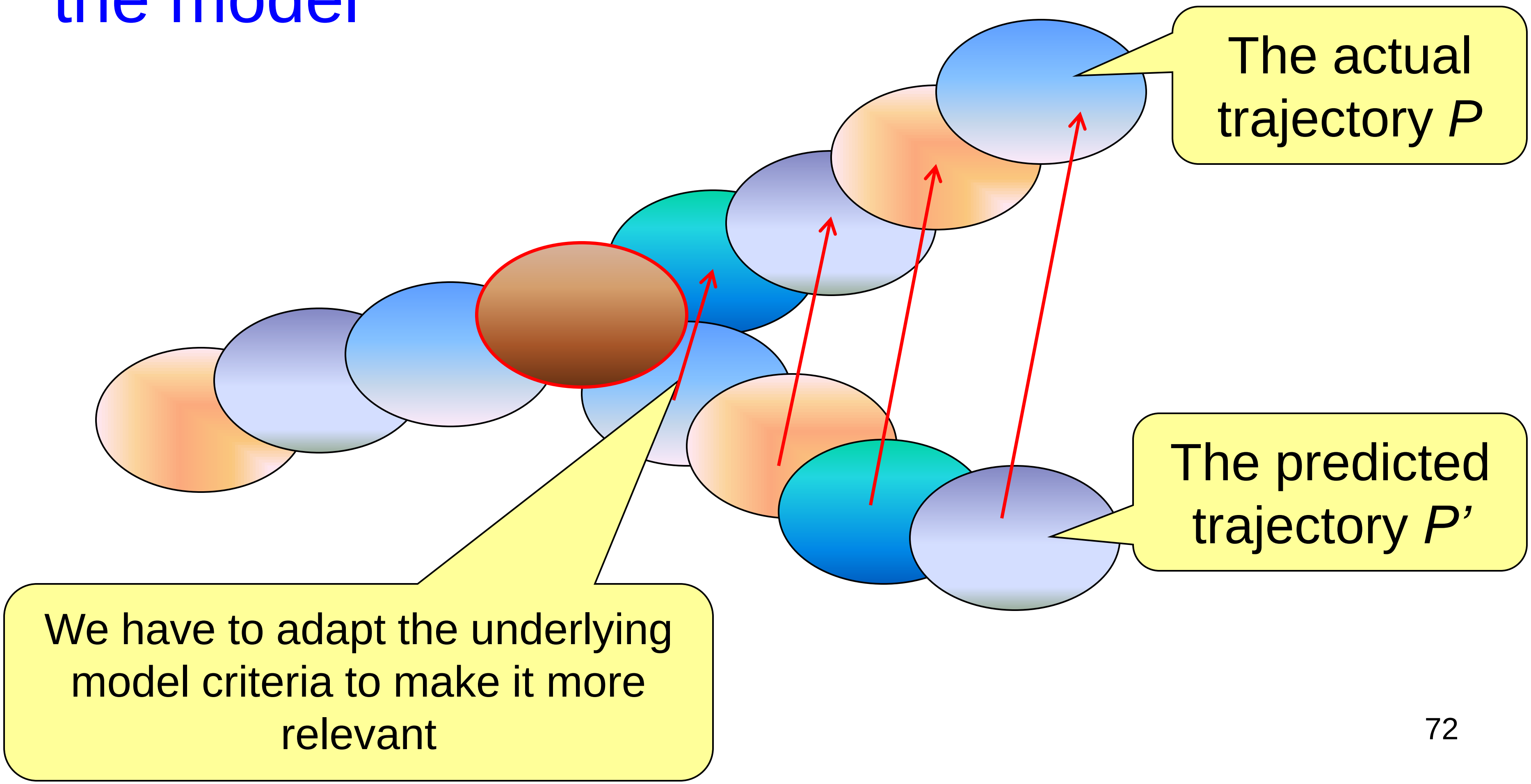
FUNCTION APPROXIMATION

Skowron, A., Stepaniuk, J., Swiniarski, R.: Approximation spaces in rough-granular computing. Fundamenta Informaticae 100 (1-4) (2010) 141-157



EXAMPLE: TRAJECTORY APPROXIMATION

Adaptation must be used to fix the deviation of the model

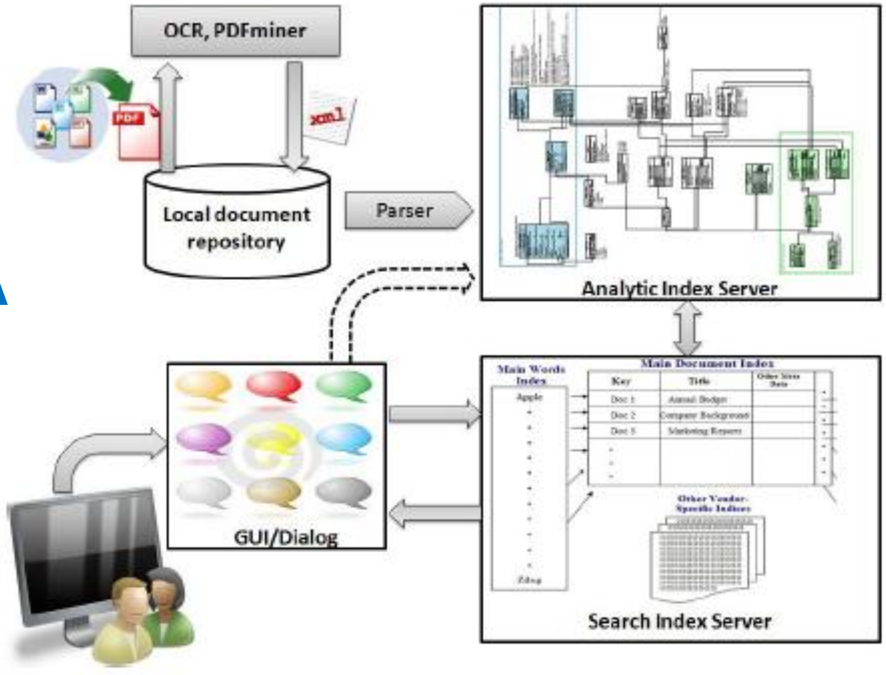


BEYOND ONTOLOGIES

EVOLVING COMMUNICATION LANGUAGE

FROM INFORMATION RETRIEVAL TO DECISION SUPPORT

SONCA



SYNAT project
H.S.Nguyen et al

BIOLOGY

[...] Tomorrow, I believe, every biologist will use computer to define their research strategy and specific aims, manage their experiments, collect their results, interpret their data, incorporate the findings of others, disseminate their observations, and extend their 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)

GOTTFRIED WILHELM LEIBNIZ

[…] If controversies were to arise, there would be no more need of disputation between two philosophers than between two accountants. For it would suffice to take their pencils in their hands, and say to each other: *Let us calculate*.

[...] Languages are the best mirror of the human mind, and that a precise analysis of the signification of words would tell us more than anything else about the operations of the understanding.

Leibniz, G.W. : Dissertio de Arte Combinatoria (1666).
Leibniz, G.W.: New Essays on Human Understanding (1705), (translated by Alfred Gideon Langley, 1896), (Peter Remnant and Jonathan Bennett (eds.)). Cambridge University Press (1982).

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)

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. Zadeh1: 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)

INTERACTIVE COMPUTATIONAL SYSTEMS (ICS)

EXAMPLES OF COMPLEX SYSTEMS

SOFTWARE PROJECTS
MEDICAL SYSTEMS
ALGORITHMIC TRADING
SYSTEMS INTEGRATING TEAMS OF ROBOTS AND HUMANS
TRAFFIC CONTROL SYSTEMS
SYSTEMS IN ACTIVE MEDIA TECHNOLOGY
PERCEPTION BASED SYSTEMS

…

CURRENT PROJECTS

- 'Interdisciplinary System for Interactive Scientific and Scientific-Technical Information' (www.synat.pl).
- Our task:
  - SONCA - an application based on a hybrid database framework, wherein scientific articles are stored and processed in various forms.
  - Semantic indexing, classification, grouping and
  - Semantic information retrieval
- Aug. 2010 -> Aug. 2013 -> Apr. 2014

- Firefighter safety

- The project aims to improve the safety of firefighters during rescue fire fighting operations, and minimalization of the effects of fire.
- The task is to create a computer system that improves the quality of
  - information flow,
  - decision-making operations
  - and the time of the rescue and fire fighting.
- From June 2013 to June 2016

PERCEPTION BASED COMPUTING

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.

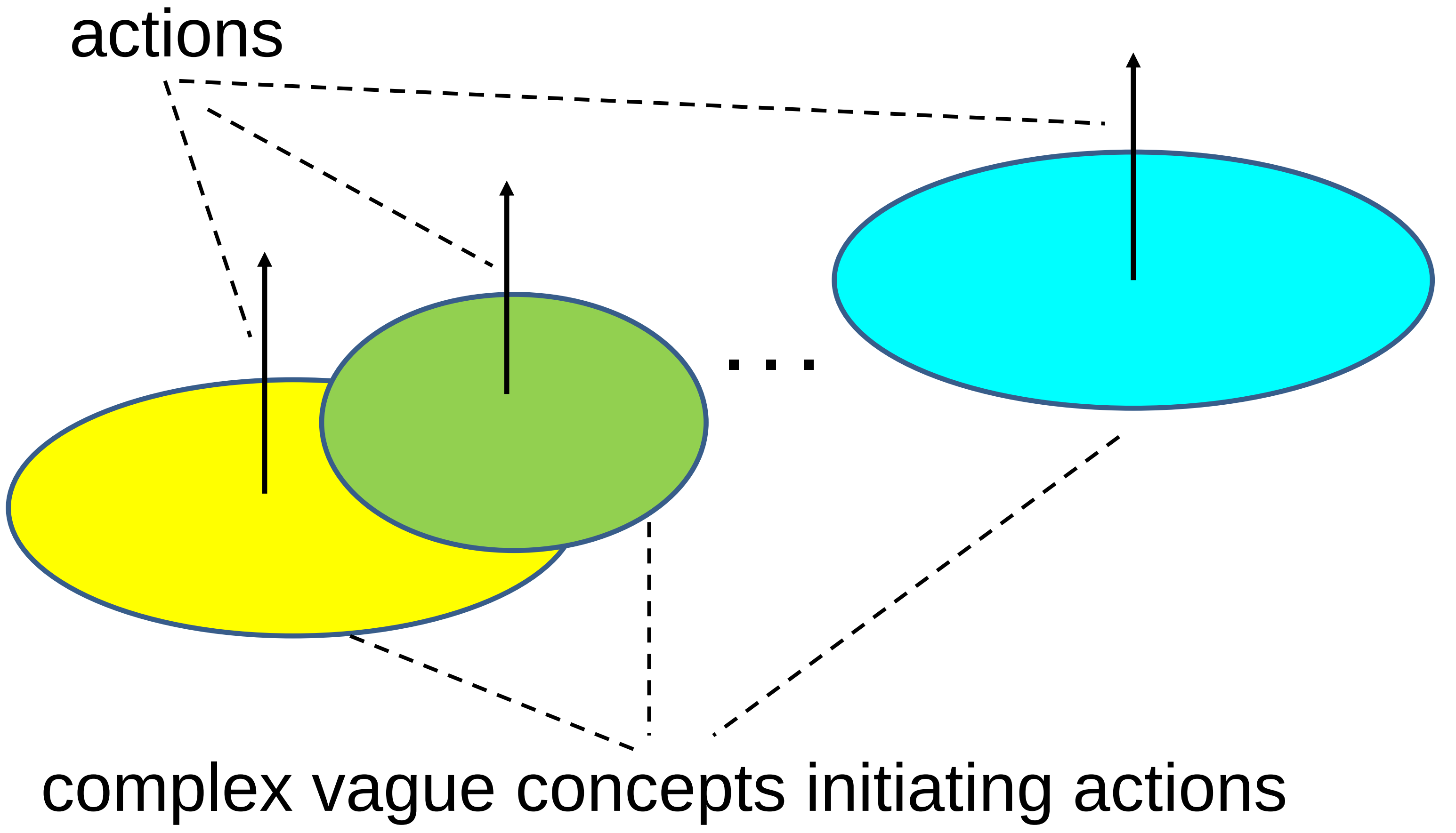
Alva Noë: Action in Perception, MIT Press 2004 interaction: agent → sensory and action attributes - only activated by agent attributes *A*(*t*) at time *t* are performing measurements and actions

history of sensory measurements and selected lower level actions over a period of time

	features of histories	higher level action
…		

	time	a_1	…	ac_1	…
x_1	1				
x_2	2				
…	…				

DISCOVERY OF COMPLEX GAMES OF INTERACTIONS



THE WITTGENSTEIN IDEA ON LANGUAGE GAMES

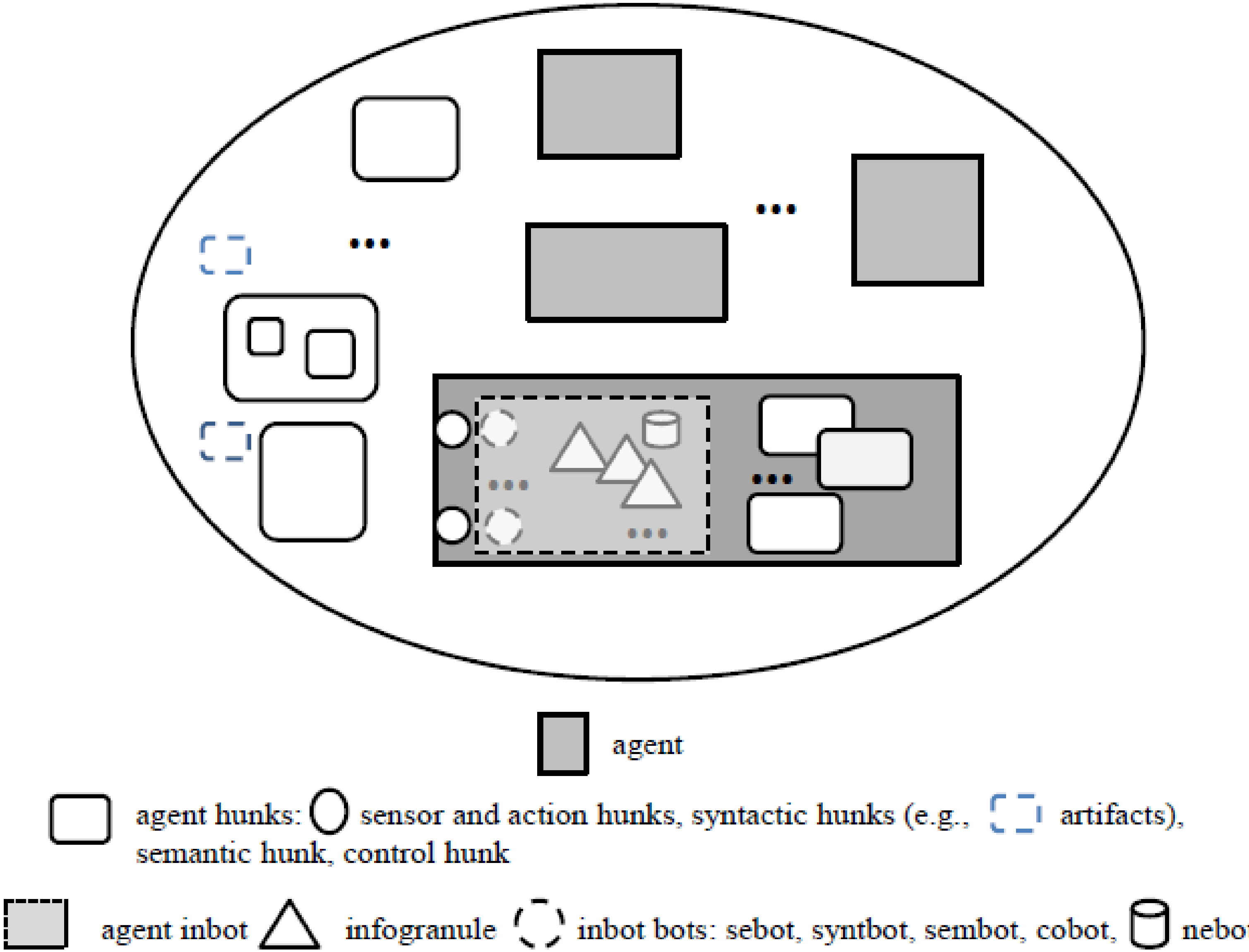
Wittgenstein, L.: Philosophical Investigations. (1953) (translated by G. E. M. Anscombe) (3rd Ed), Blackwell Oxford1967

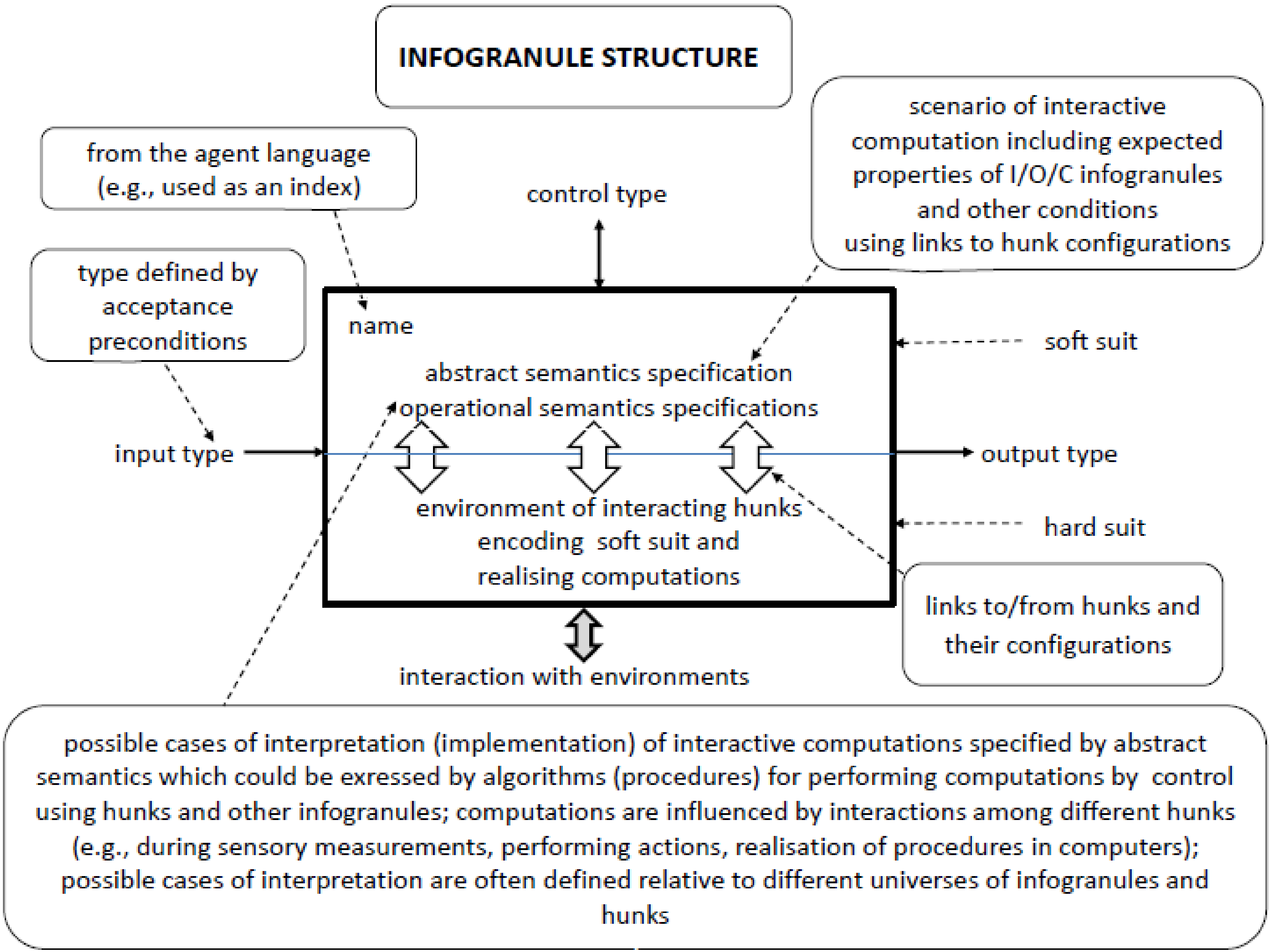
Granules

information granules (infogranules)

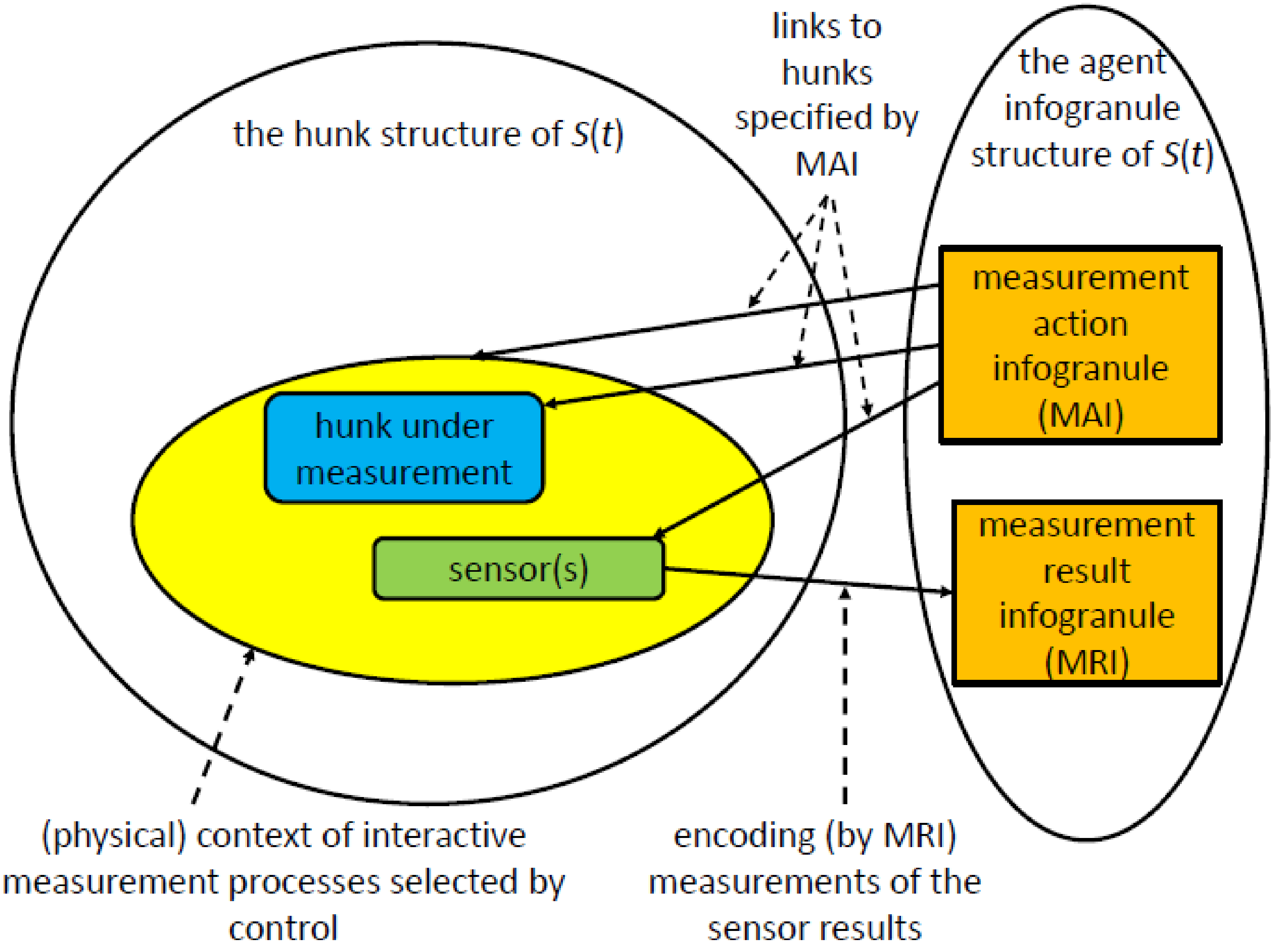
physical granules (hunks)

STATES IN INTERACTIVE COMPUTATIONAL MODELS



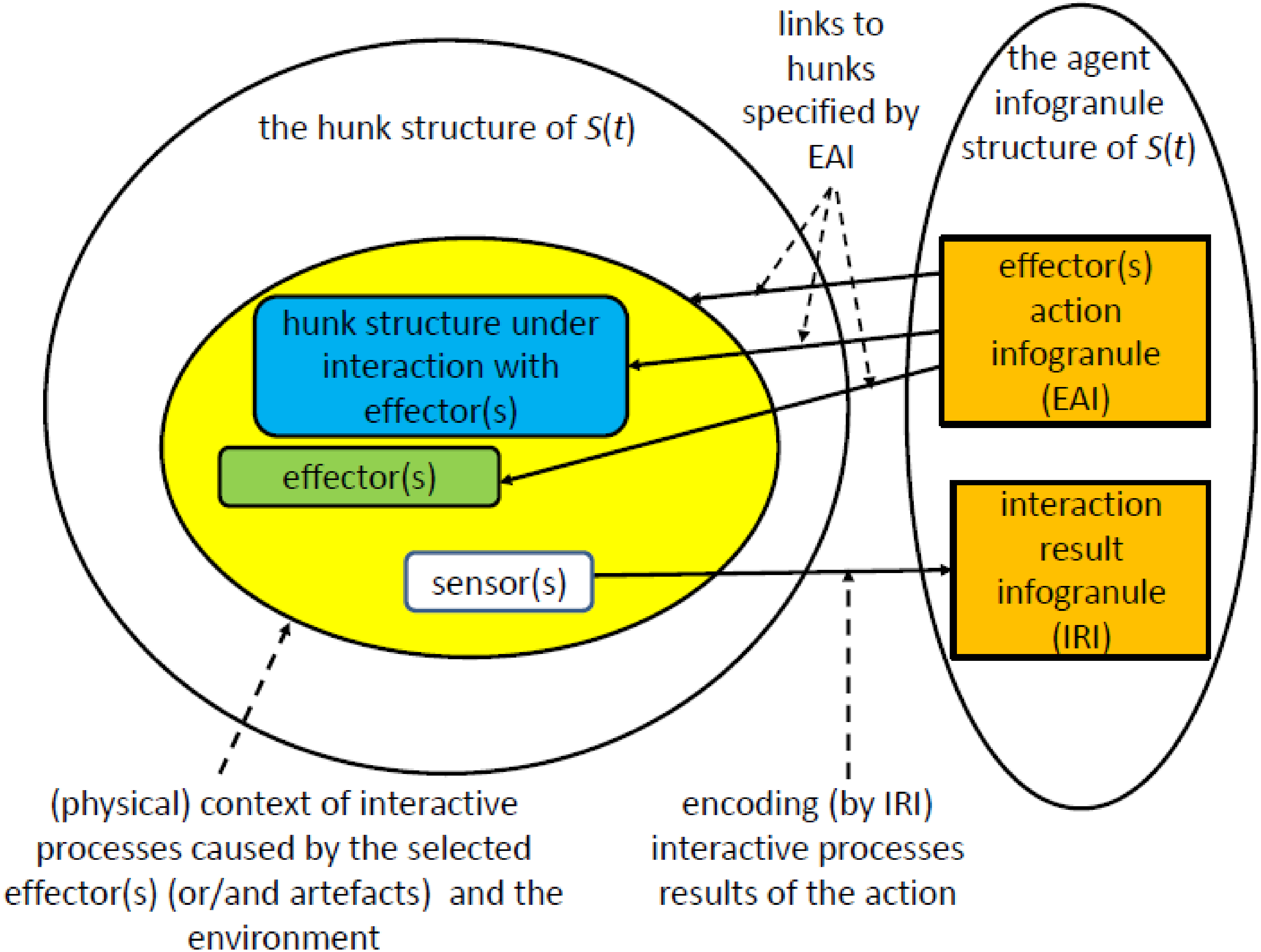

INFOGRANULE STRUCTURE
from the agent language (e.g., used as an index)
control type
scenario of interactive computation including expected properties of I/O/C infogranules and other conditions using links to hunk configurations
type defined by acceptance preconditions
name
soft suit
abstract semantics specification
operational semantics specifications
input type
output type
environment of interacting hunks encoding soft suit and realising computations
hard suit
links to/from hunks and their configurations
interaction with environments
possible cases of interpretation (implementation) of interactive computations specified by abstract semantics which could be exressed by algorithms (procedures) for performing computations by control using hunks and other infogranules; computations are influenced by interactions among different hunks (e.g., during sensory measurements, performing actions, realisation of procedures in computers); possible cases of interpretation are often defined relative to different universes of infogranules and hunks

SENSORS



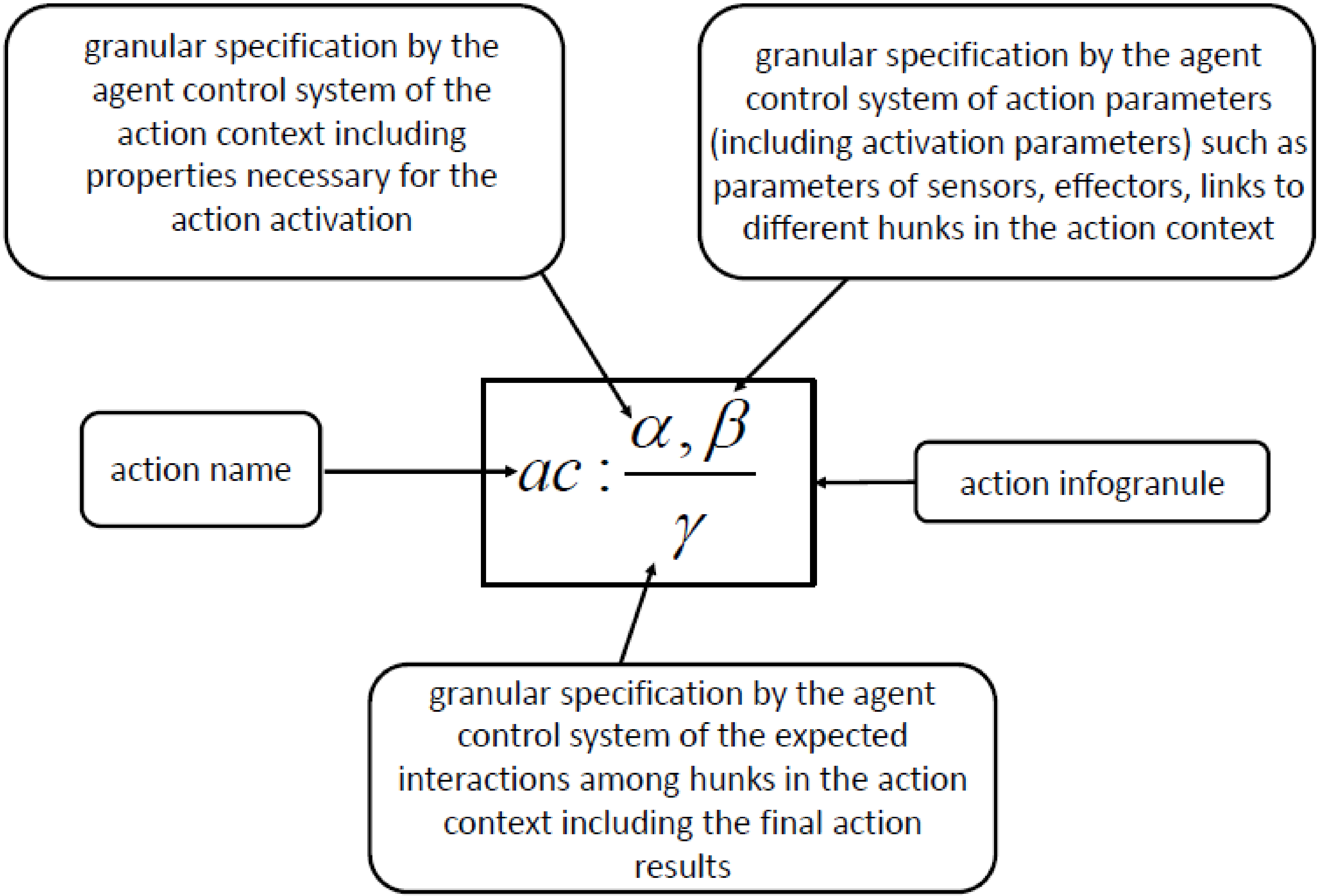
the hunk structure of $S(t)$
links to hunks specified by MAI
the agent infogranule structure of $S(t)$
measurement action infogranule (MAI)
hunk under measurement
sensor(s)
measurement result infogranule (MRI)
(physical) context of interactive measurement processes selected by control
encoding (by MRI) measurements of the sensor results

ACTION

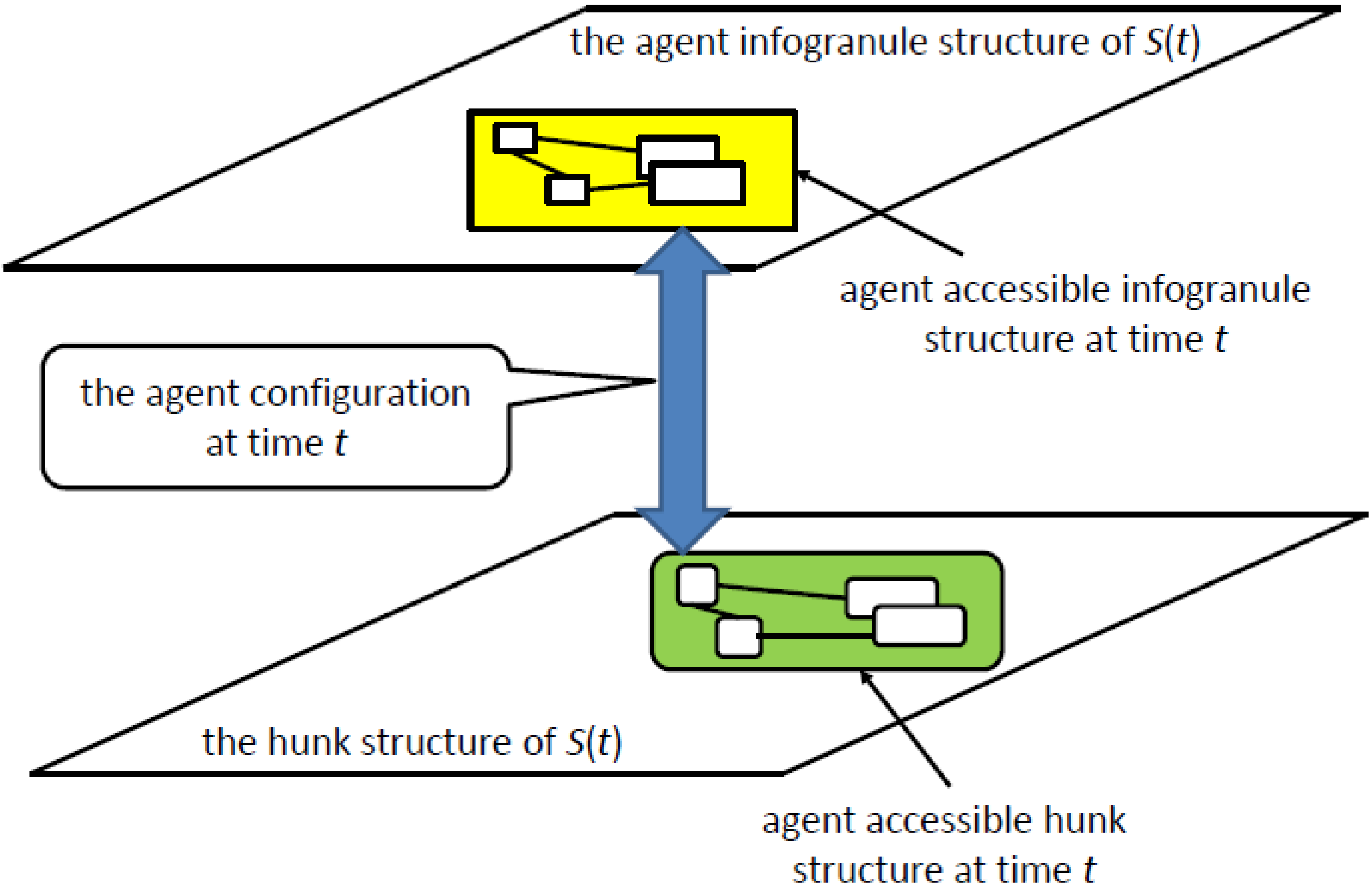


links to hunks specified by EAI
the agent infogranule structure of S(t)
the hunk structure of S(t)
effector(s) action infogranule (EAI)
hunk structure under interaction with effector(s)
effector(s)
interaction result infogranule (IRI)
sensor(s)
(physical) context of interactive processes caused by the selected effector(s) (or/and artefacts) and the environment
encoding (by IRI) interactive processes results of the action

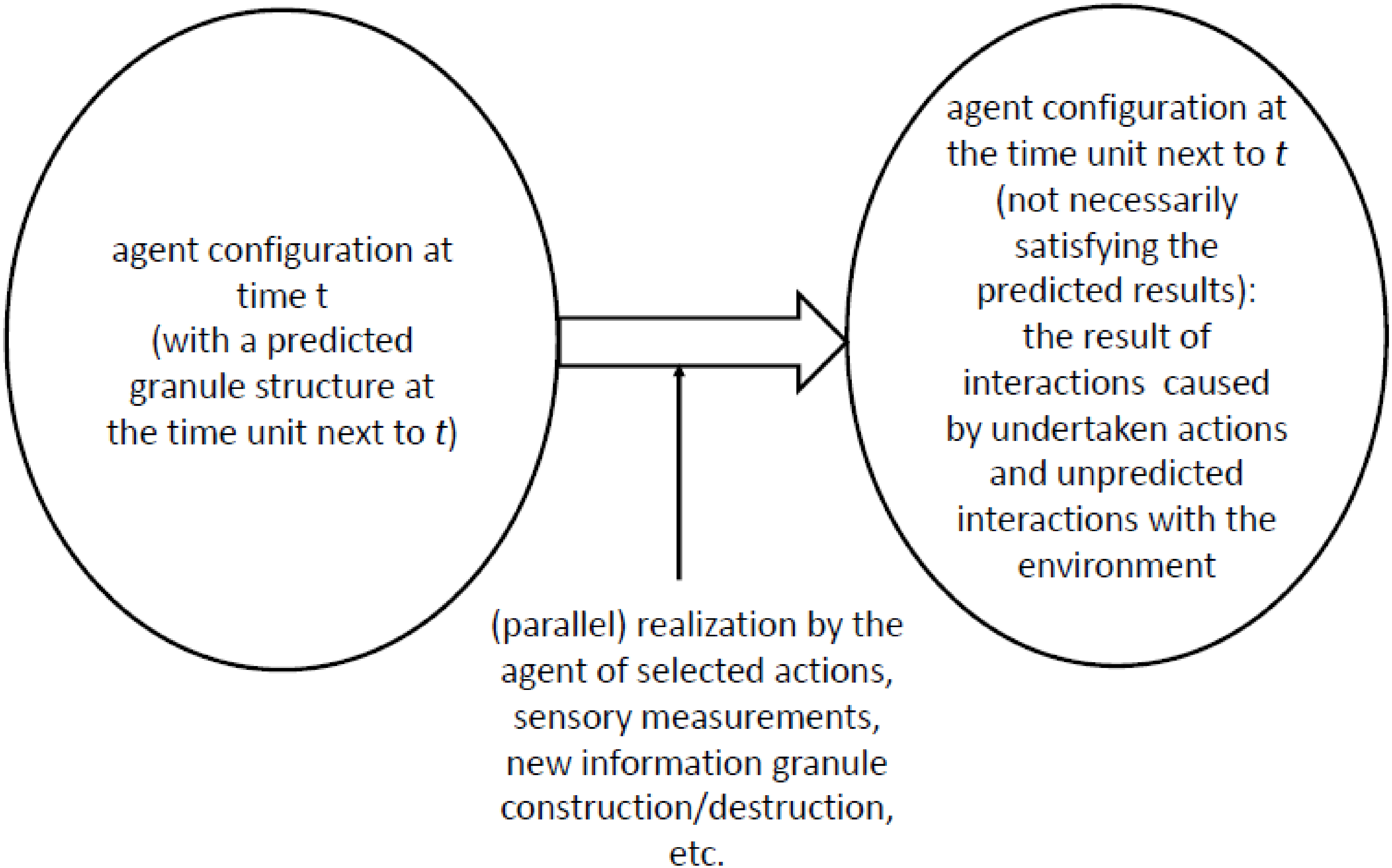
ACTION


granular specification by the agent control system of the action context including properties necessary for the action activation
granular specification by the agent control system of action parameters (including activation parameters) such as parameters of sensors, effectors, links to different hunks in the action context
action name
$ac : \frac{\alpha, \beta}{\gamma}$
action infogranule
granular specification by the agent control system of the expected interactions among hunks in the action context including the final action results

CONFIGURATION

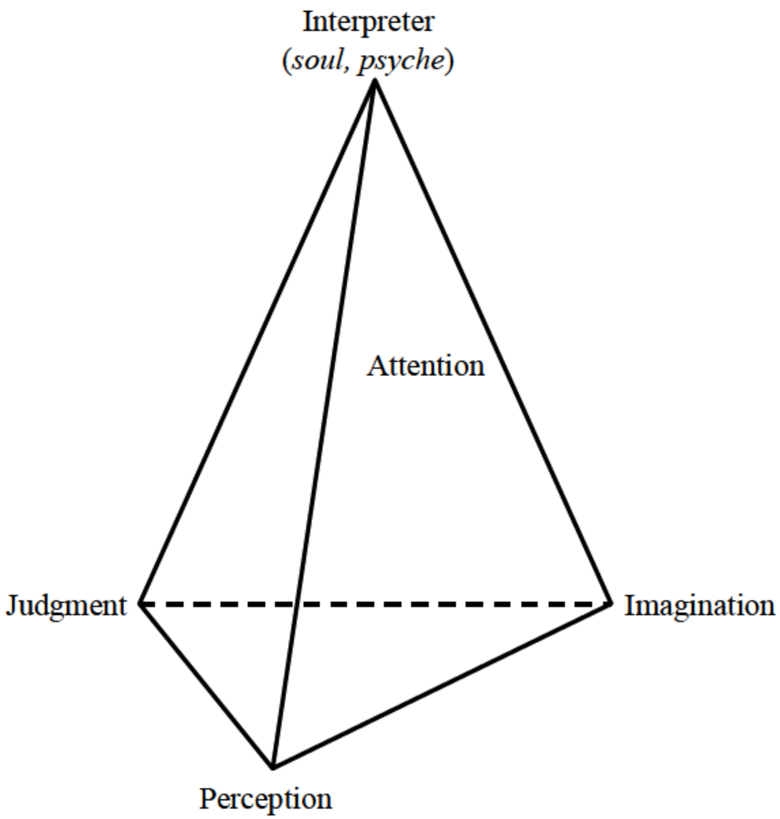


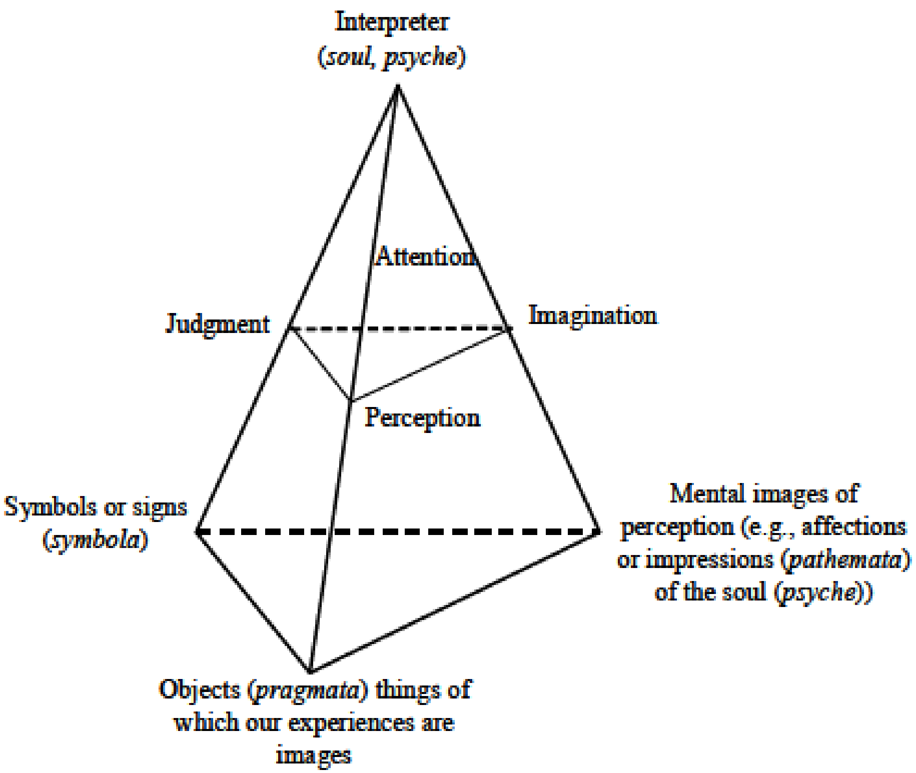
TRANSITION RELATION



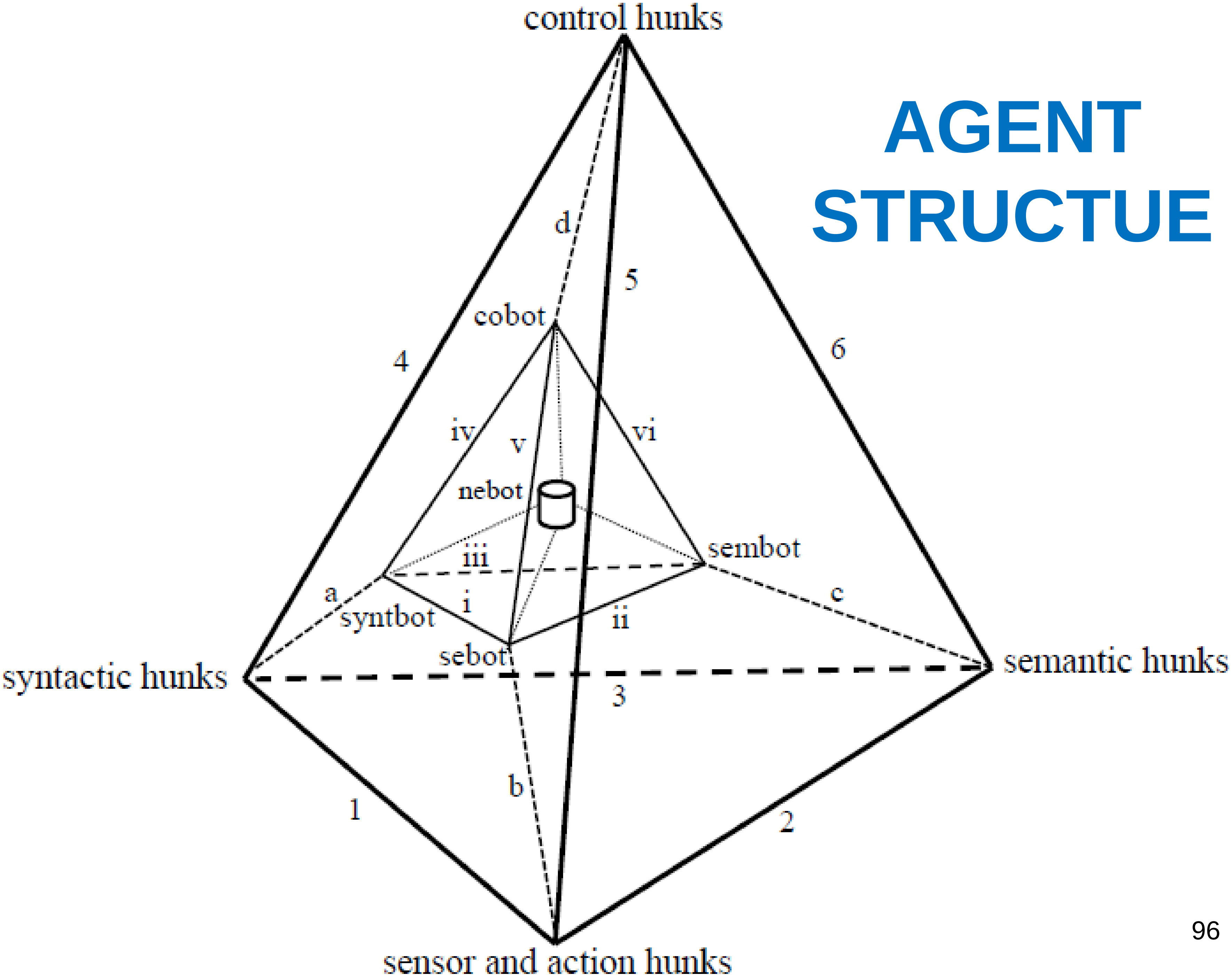
Aristotle has dedicated many papers to clarify the relationships between concepts such as thinking, imagination, judgment, perception and psyche issue:

Thinking is different from perceiving and is held to be in part imagination, in part judgment: we must therefore first mark off the sphere of imagination and then speak of judgment.

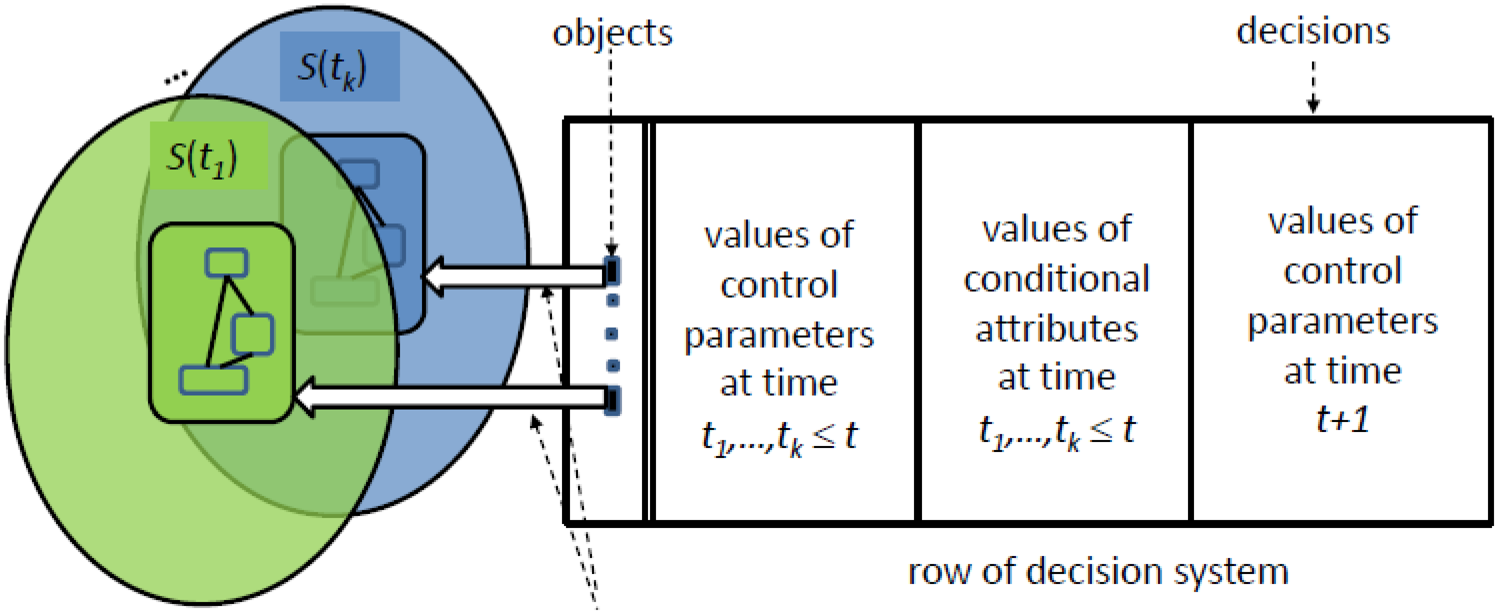




AGENT STRUCTUE



INTERACTIVE INFORMATION AND DECISION SYSTEMS

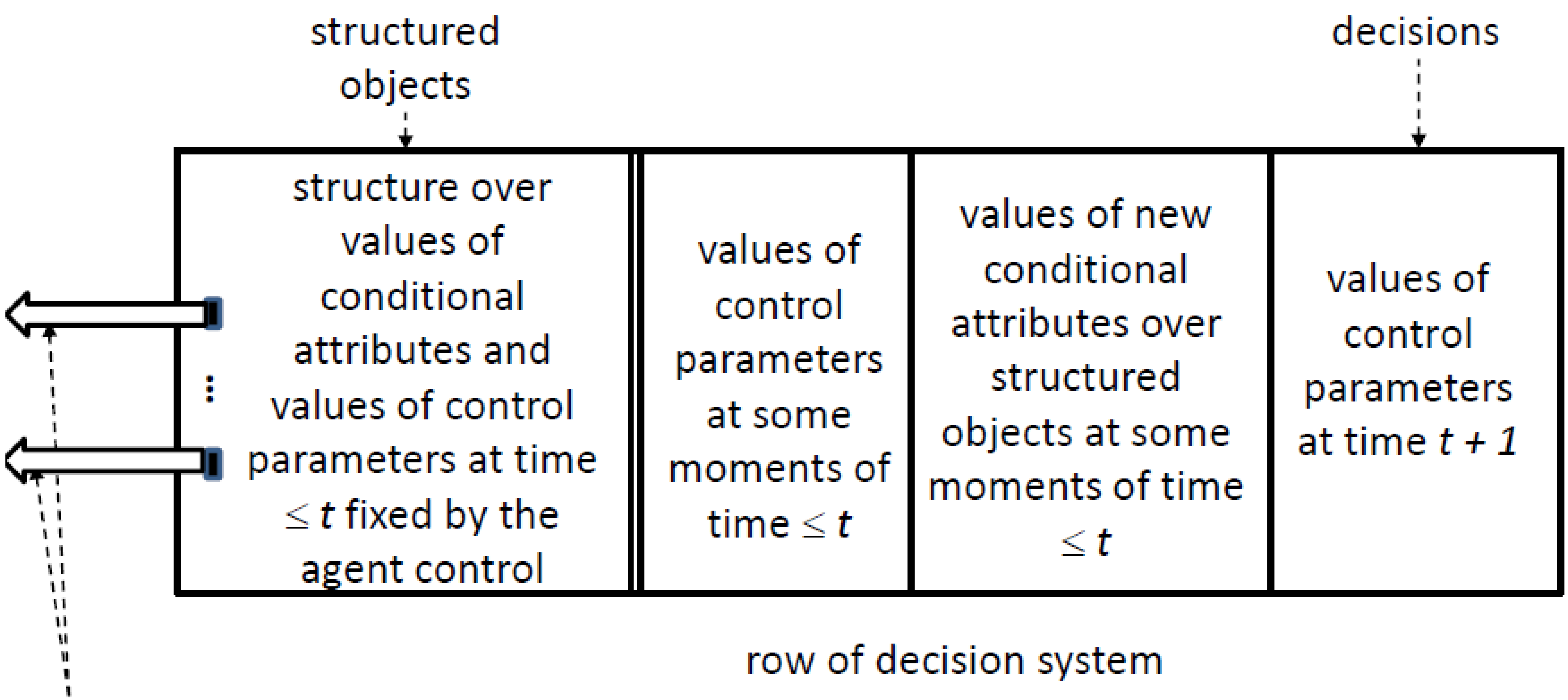


links to parts of a structure of hunks in global states defined by the agent control system at time $t_1,\ldots,t_k \leq t$

using the agent knowledge bases and, in particular, parameters of the (actual at time $t_1,\ldots,t_k$) agent mereology, relations on values of control parameters at time t and/or values of conditional attributes at time t;

the structure of hunks in global states is defined by agent control using some constraints over values of conditional attributes and/or control parameters

INTERACTIVE INFORMATION AND



links to parts of a structure of hunks in global states defined by the agent control system at at some moments of time ≤ *t*
using the agent knowledge bases and, in particular, parameters of the (actual at at some moments of time ≤ *t*) agent mereology, relations on values of control parameters at time *t* and/or values of conditional attributes at time *t*;
the structure of hunks in global states is defined by agent control using some constraints over values of conditional attributes and/or control parameters

HOW TO CONTROL COMPUTATIONS IN ICS ?

***

RISK MANAGEMENT IN ICS

Jankowski, A., Skowron, A., Wasilewski, P.: Interactive Computational Systems. CS&P 2012
Jankowski, A., Skowron, A., Wasilewski, P.: Risk Management and Interactive Computational Systems. Journal of Advanced Mathematics and Mathematics 2012

THREATS AND VULNERABILITIES

- Threat
  - **A potential occurrence that can have an undesirable effect on the system assets of resources**
  - Results in breaches in confidentiality, integrity, or a denial of service, e.g., outsider penetrating a system is an outsider threat
  - Need to identify all possible threats and address them to generate security objectives
- Vulnerability
  - **A weakness that makes it possible for a threat to occur**

'vulnerability' refers to **the capacity to be wounded, i.e., the degree to which a system is likely to experience harm due to exposure to a hazard** Turner II, B.L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Kasperson, J.X., Luers, A., Martello, M.L., Polsky, C., Pulsipher, A., Schiller, A., 2003. A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences of the United States of America 100, 8074–8079. (Turner II et al., 2003)

THREATS AND VULNERABILITIES

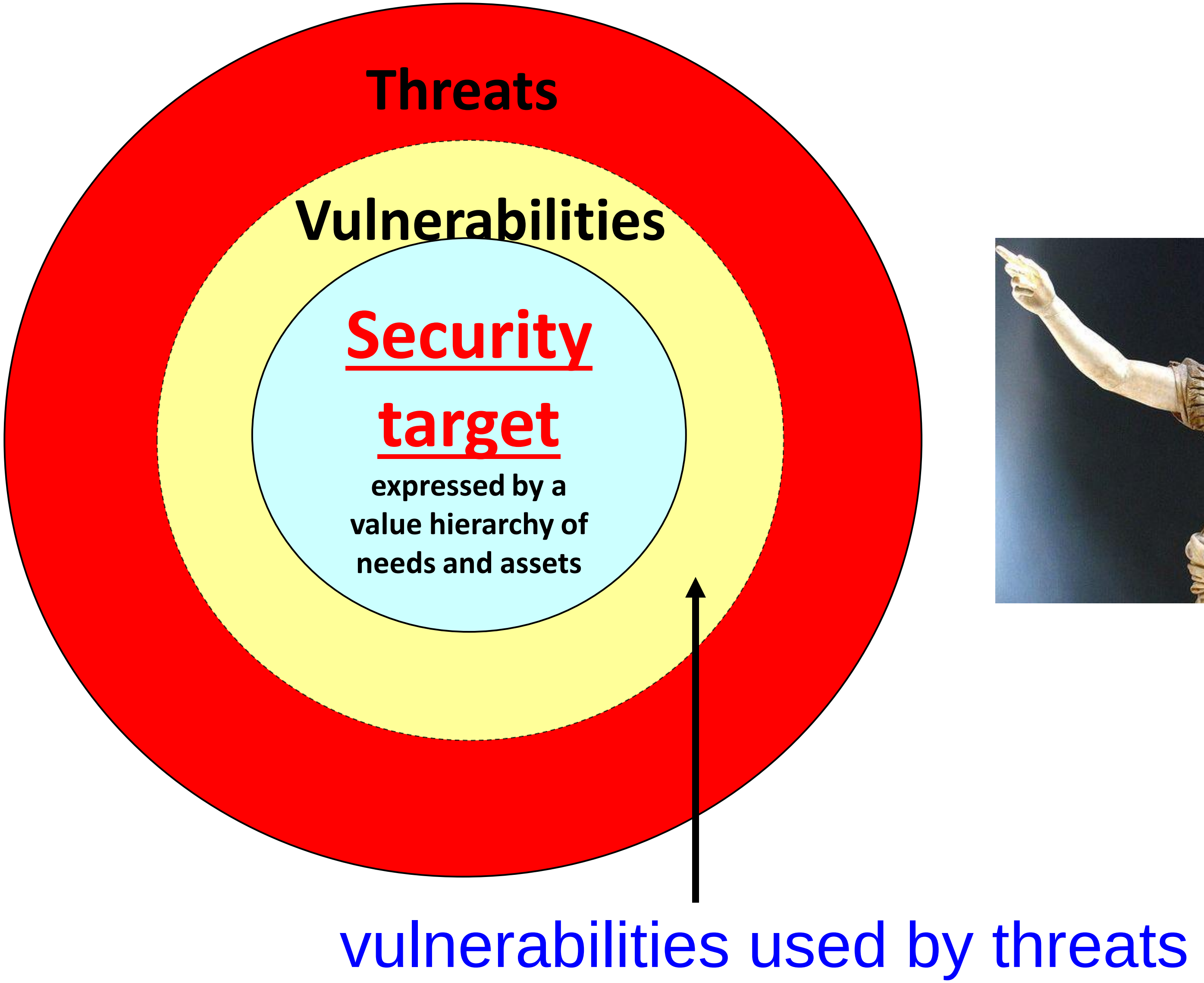
THREATS AND VULNERABILITIES

Security target

expressed by a value hierarchy of needs and assets

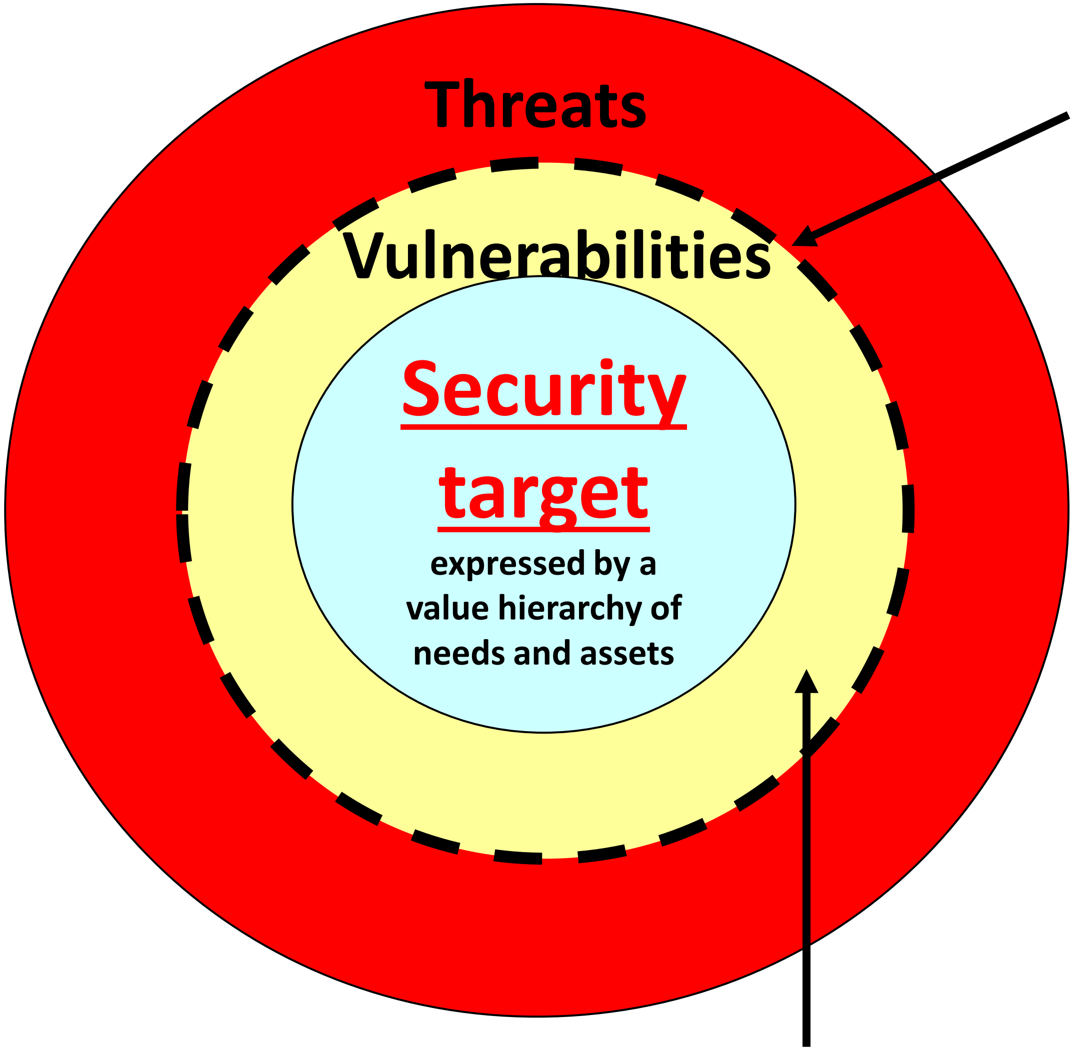
THREATS AND VULNERABILITIES

THREATS AND VULNERABILITIES



THREATS AND VULNERABILITIES

controls

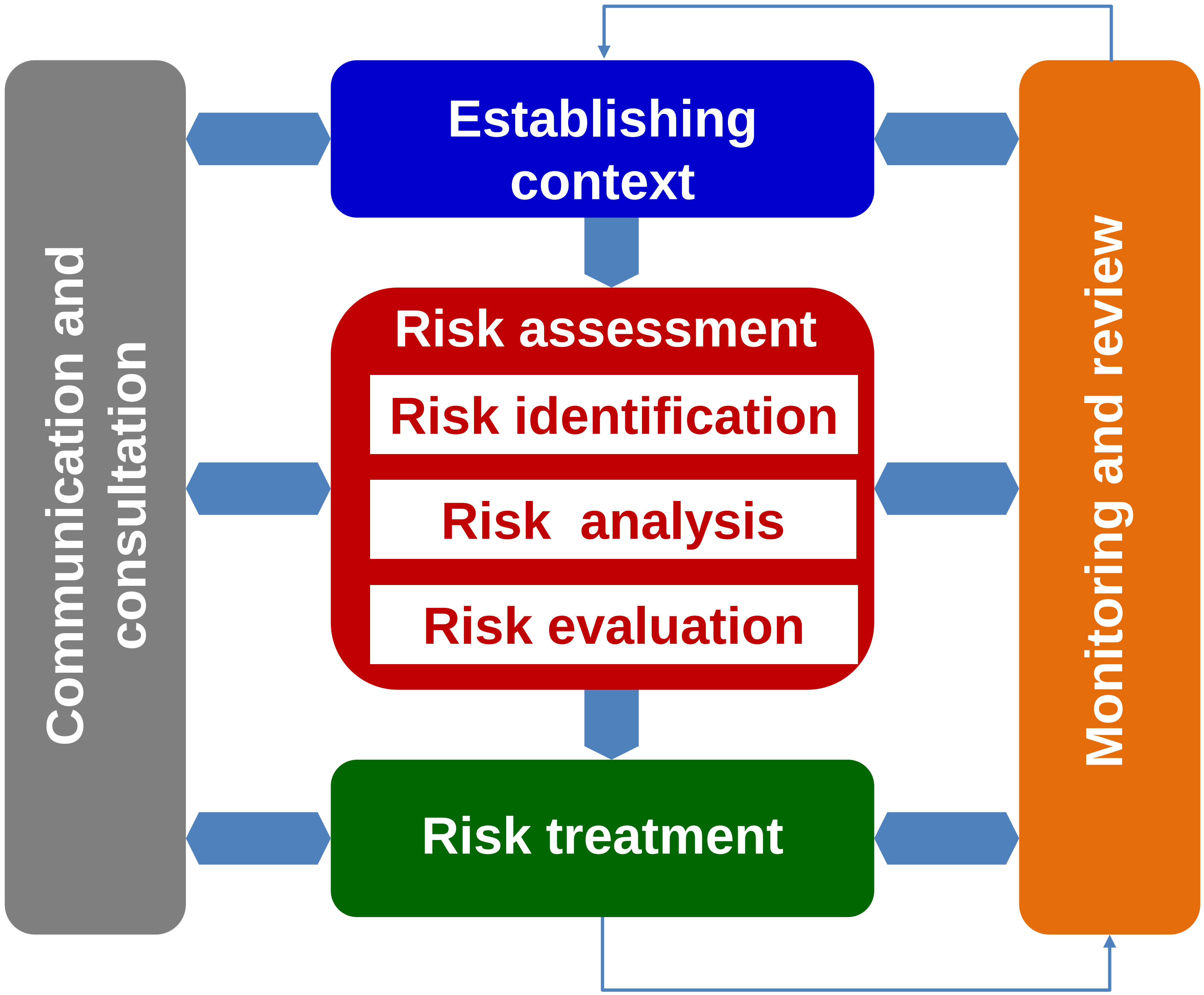


vulnerabilities used by threats

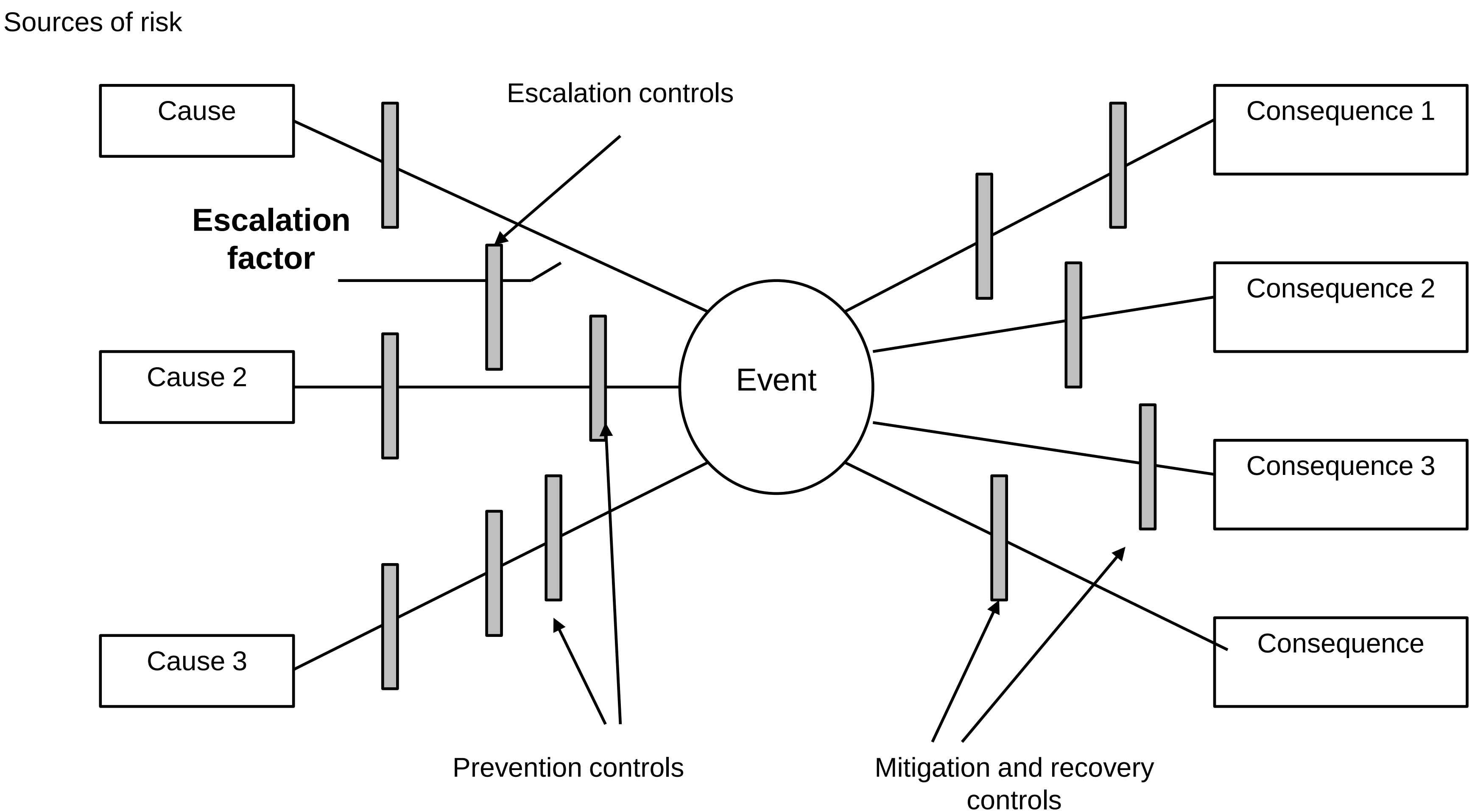
EXAMPLE OF A PROBABILITY CRITERIA MATRIX

Likelihood rating							
	E	IV	III	II	I	I	I
	D	IV	III	III	II	I	I
	C	V	IV	III	II	II	I
	B	V	IV	III	III	II	I
	A	V	V	IV	III	II	II
		1	2	3	4	5	6
		Consequence rating					

RISK MANAGEMENT PROCESS

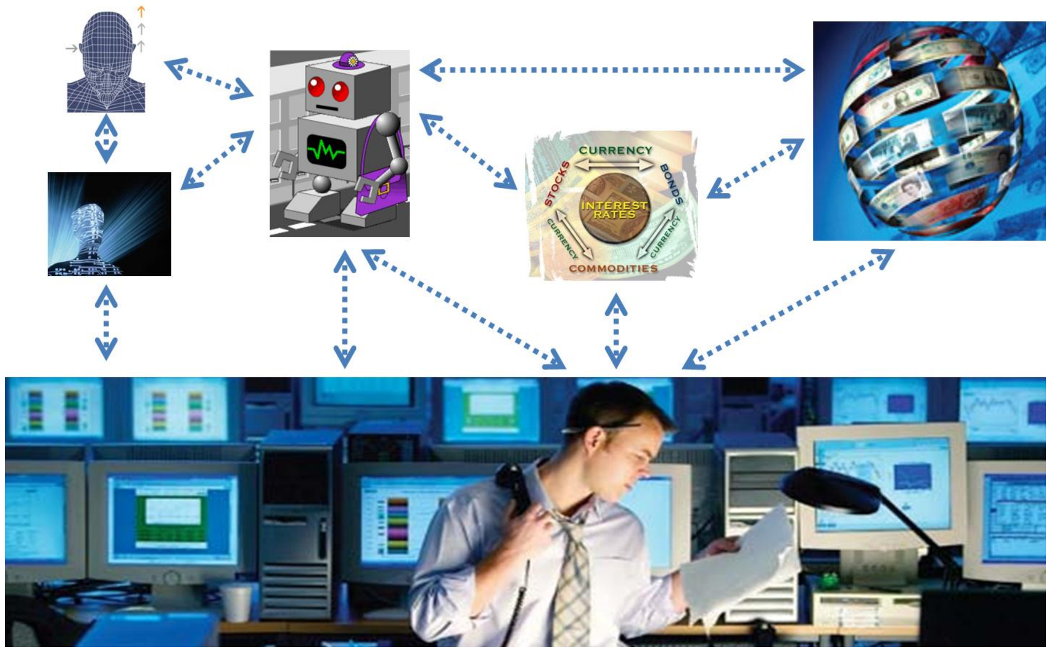


EXAMPLE OF BOW TIE DIAGRAM FOR UNWANTED CONSEQUENCES



ALGORITHMIC TRADING

THE CONCEPT OF TRADING ROBOTS

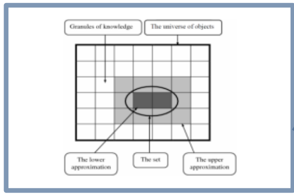


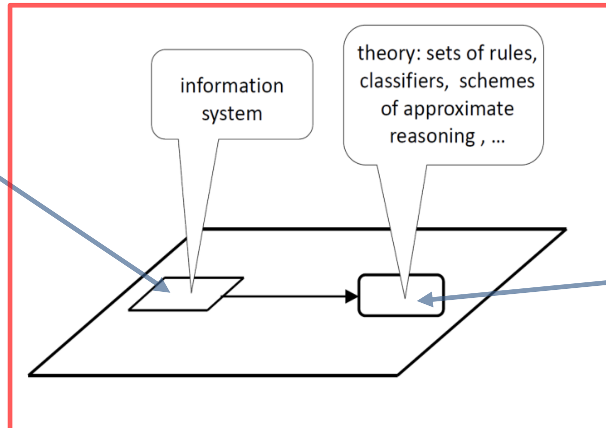
The **trading robots** system, is the use of electronic financial markets platforms for entering trading orders with an algorithm deciding on basic aspects of the order such as the asset, timing, price, or quantity of the order, or in many cases initiating the order without human intervention.

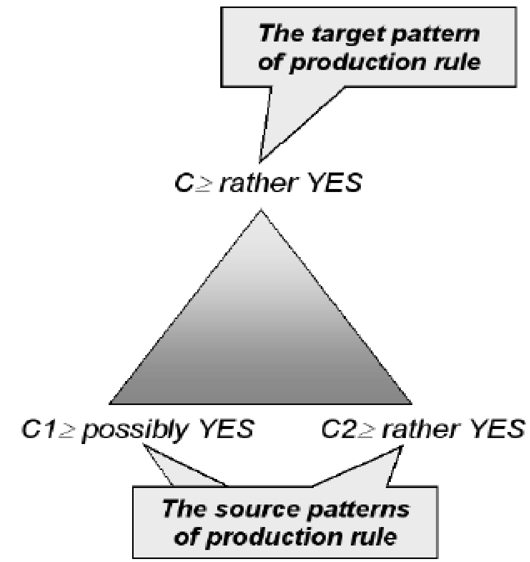
The concept of such type of use of software is also known as robo trading or algorithmic trading or automated trading, also algo trading, black-box trading

Based on definition from: http://en.wikipedia.org/wiki/Algorithmic_trading

PEARL'S POSTULATE: a science-friendly language for articulating causal knowledge about market crash & a mathematical machinery for processing that knowledge combining it with data and drawing new causal conclusions



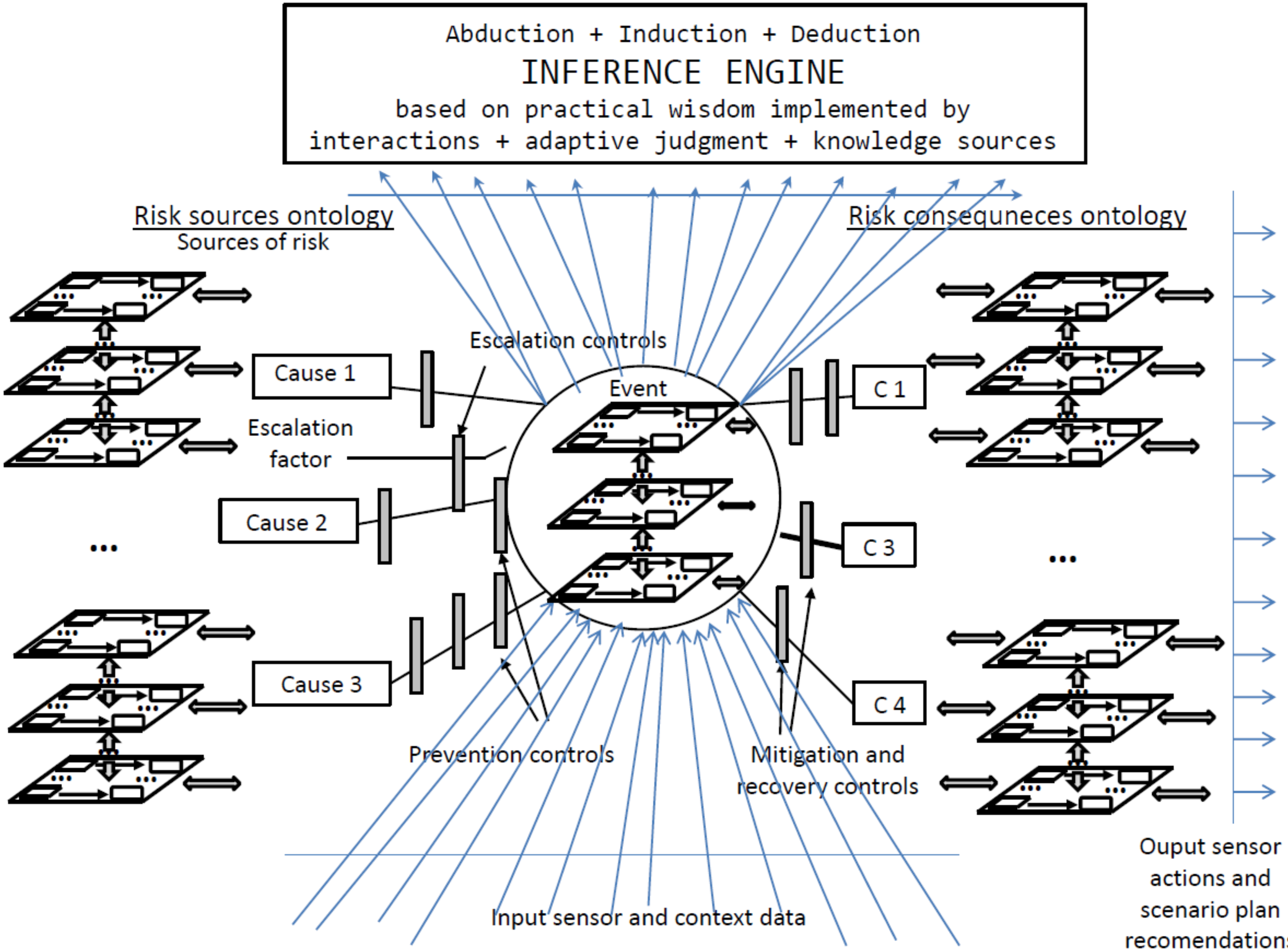




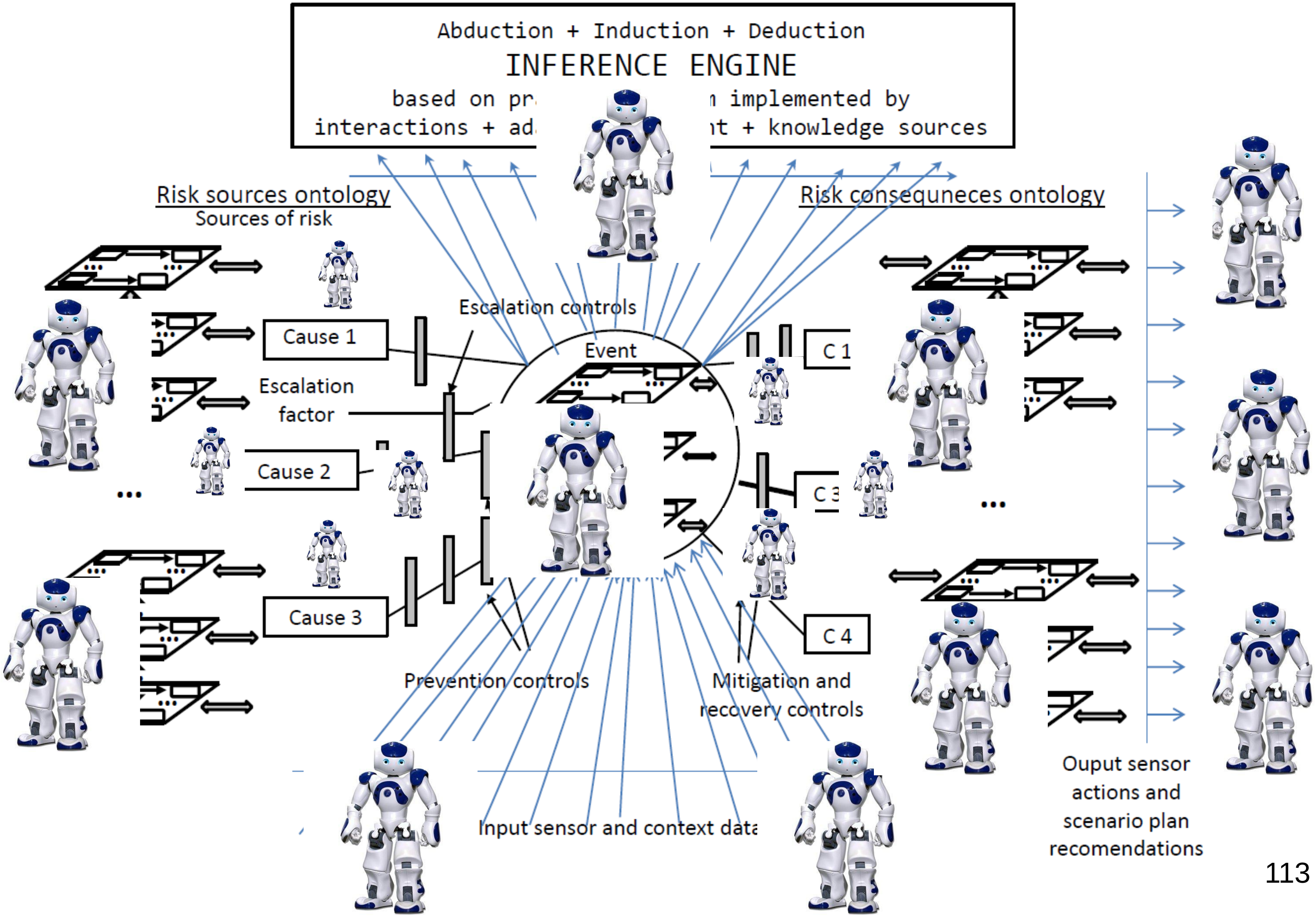
$$(P_1 = 1) \to (P_4 = 1)$$
$$(P_2 = 2) \to (P_4 = 1)$$
$$(P_1 = 2) \wedge (P_2 = 0) \to (P_4 = 1)$$
$$(P_3 = 0) \wedge (P_2 = 0) \to (P_4 = 1)$$

Agent logic based on Interactive Information System + Theory

THE ESSENCE OF ADGAM GROUP TECHNOLGICAL SOLUTIONS FOR ALGORITHMIC TRADING



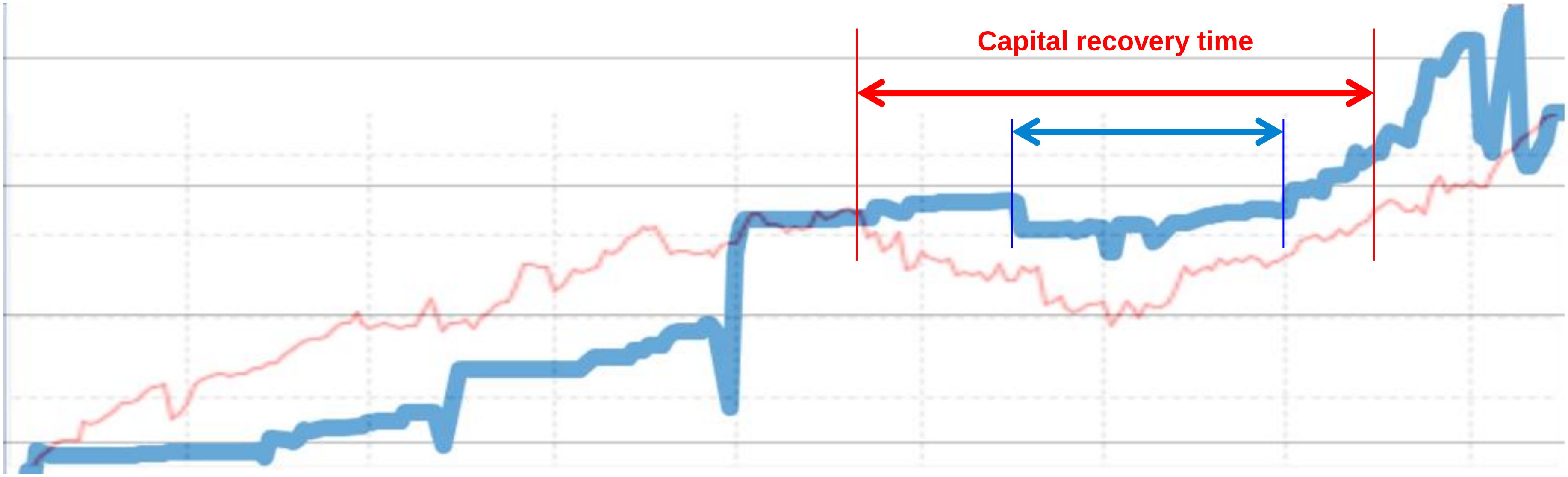
THE ESSENCE OF ADGAM GROUP TECHNOLGICAL SOLUTIONS FOR ALGORITHMIC TRADING

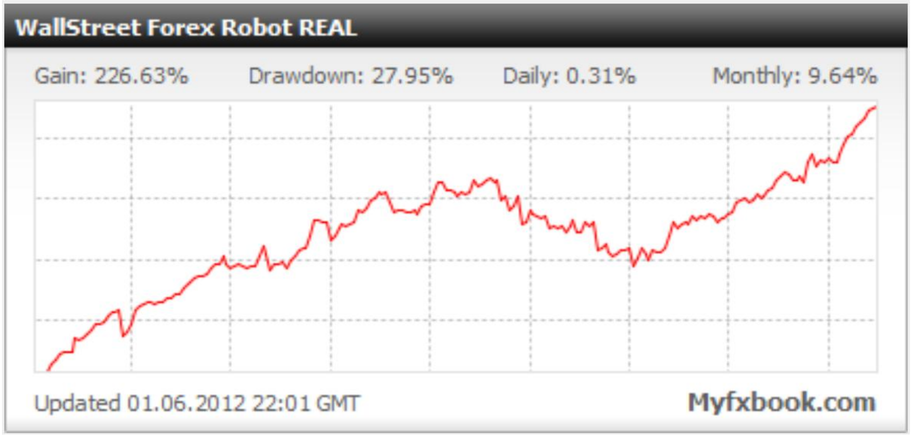


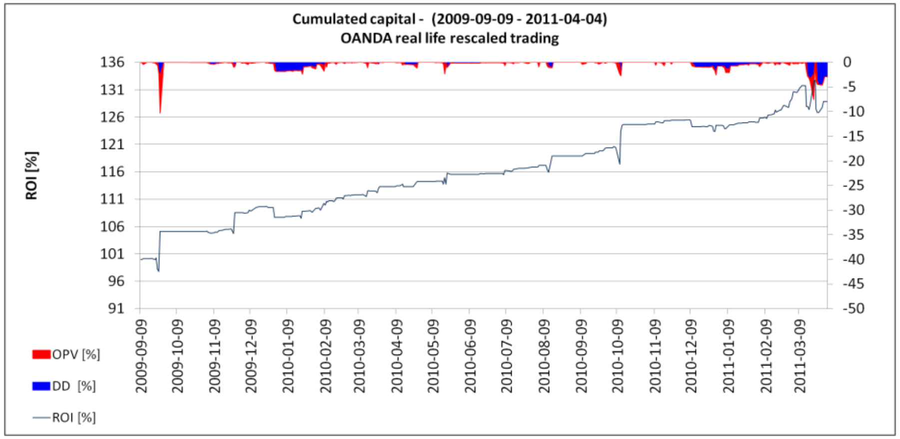
ADGAM GROUP EFFORTS ON THE DEVOLOPMENT OF ALGORITHMIC TRADING TECHNOLOGY

Project duration [years]	**5**
man – months	1 000
mathematical models implemented	100
experiments tested on many years historical data and many thousands of years of Monte Carlo generated data	1000
lines of code	300 000

REAL-MONEY Account Live Trading by rescaled AdgaM TRADING ROBOTS & WALLSTREET FOREX ROBOT







The essence of algorithmic trading based on AdgaM Group experience

The essence of algorithmic trading

Causal inference supporting market crash forecast is not easy task

The essence of algorithmic trading

Causal inference supporting market crash forecast is not easy task

„Those of us who have looked to the self-interest of lending institutions to protect shareholders' equity, myself included, are in a state of shocked disbelief....

The whole intellectual edifice

[of risk-management in financial markets]….

collapsed last summer."

Alan Greenspan

former Fed chairman

at a congressional hearing in October 2008.

Causal inference supporting market crash forecast is not easy task

Pearl's postulate

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

1. a science-friendly language for articulating causal knowledge about market crash

&

2. a mathematical machinery for processing that knowledge, combining it with data and drawing new causal conclusions about a phenomenon.

CHALLENGES SUMMARY

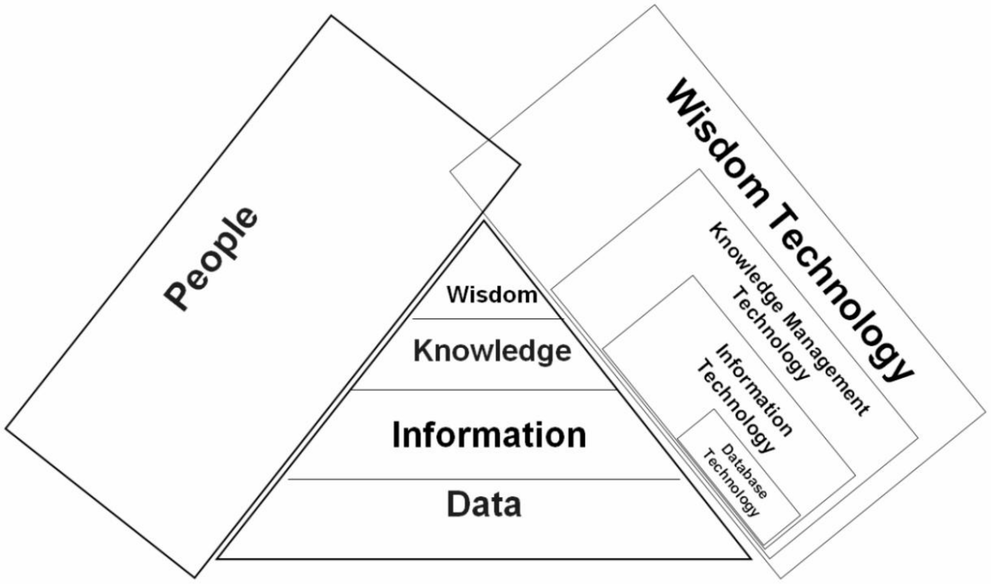
- RS & INTRACTIVE COMPUTATIONS
  - MODELING OF INTERACTIVE COMPUTATIONS
    - GENERALIZED INFORMATION SYSTEMS
      - INTERACTIVE INFORMATION SYSTEMS
      - HIERARCHIES AND NETWORKS OF INFORMATION SYSTEMS
      - CONTEXT DEPENDENT INFORMATION SYSTEMS
      - DYNAMICAL NETWORKS OF INFORMATION SYSTEMS
  - CONTROL OF INTERACTIVE COMPUTATIONS
- RS & ADAPTIVE JUDGMENT
  - LEARNING HIERARCHIES OF INFORMATIOIN SYSTEMS
  - LERNING HIERARCHIES OF SATISFIABILITY RELATIONS
  - NEW FEATURE DISCOVERY
  - REASONING ABOUT CHANGES
    - ROUGH CALCULUS
    - STRATEGIES FOR ADAPTATION OF APPROXIMATION SPACES
  - CONTEXT DISCOVERY
- RS & EVOLUTION OF COMMUNICATION LANGUAGE
  - LEARNING NEW FEATURES, PHRASES, SENTENCES, SITUATION DESCRIPTION
  - LEARNING SCHEMES OF REASONING AND COMPOSITIONS OF RULES
  - LEARNING INCLUSION RELATION IN INTERACTION WITH USERS (EXPERTS)
  - LEARNING OF COALITIONS AND ORGANIZATIONS
  - AUTONOMIC LEARNING, SELF ORGANIZATION
  - RISK MANAGEMENT IN INTERACTIVE COMPUTATIONAL SYSTEMS
- RS & SCALABILITY
  - PARALLEL ALGORITHMS
  - EMBEDDED HARDWARE
  - CLOUD COMPUTING

WISDOM TECHNOLOGY (WisTech)

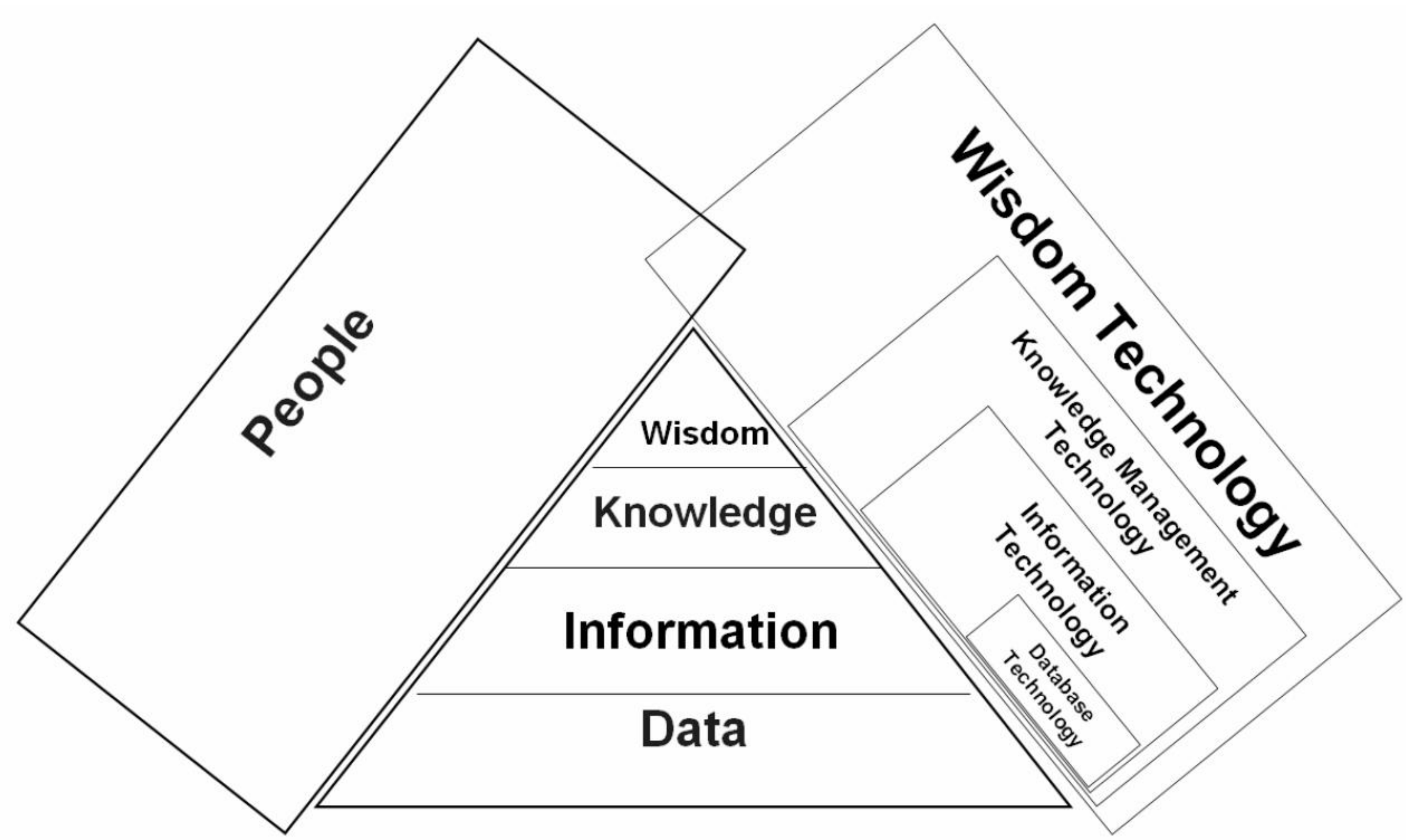
A. Jankowski, A. Skowron: A wistech paradigm for intelligent systems, Transactions on Rough Sets VI: LNCS Journal Subline, LNCS 4374, 2007, 94–132

A. Jankowski A., Skowron A.: Logic for artificial intelligence: The Rasiowa-Pawlak school perspective, In: Ehrenfeucht, A., Marek V., Srebrny M. (Eds.) Andrzej Mostowski and Foundational Studies, IOS Press, Amsterdam, 2008, 106-143.

WISDOM= INTERACTIONS + ADAPTIVE JUDGMENT + KNOWLEDGE BASES



IRGC = systems based on interactive computations on granules with use of domain (expert) knowledge, process mining and concept learning


People
Wisdom
Knowledge
Information
Data
Wisdom Technology
Knowledge Management Technology
Information Technology
Database Technology

THANK YOU !

APPENDIX

REFERENCES AND FURTHER READINGS

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Skowron, A., Suraj, Z. (eds.): Rough Sets and Intelligent Systems. Professor Zdzislaw Pawlak in Memoriam. Series Intelligent Systems Reference Library 42-43, Springer (2013)

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International Rough Set Society
http://www.roughsets.org

Group at Warsaw University:

http://logic.mimuw.edu.pl

RSES: http://logic.mimuw.edu.pl/~rses/

Rough Set Database System:

http://rsds.univ.rzeszow.pl/

Journal: Transactions on Rough Sets

http://roughsets.home.pl/www/index.php?option=com_content&task=view&id=14&Itemid=32

http://scholar.google.com/citations?user=fYu9ryIAAAAJ&hl=en&oi=ao

http://scholar.google.com/citations?user=zVpMZBkAAAAJ&hl=en&oi=ao