APPROXIMATE REASONING IN MAS: Rough Set Approach

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CHALLENGE

Make progress in developing methods for complex concept approximations and reasoning about approximated concepts in distributed environments.
AGENDA

ROUGH SETS
&
GRANULAR COMPUTING
&
LAYERED LEARNING
&
DOMAIN ONTOLOGY APPROXIMATION

FOR COMPLEX CONCEPT APPROXIMATION
Examples of complex concepts

- Dangerous situation
- Identification of behavioral patterns
- Risk patterns
- Similarity of plans
- Sunsopt classification
- Outliers
- Reinforcement learning: conditions for actions
- Intentions, motivations, desires, beliefs,...
- ...
ROUGH SETS
over 4000 publications

Prof. Zdzisław Pawlak
passed away on
April 7, 2006
KNOWLEDGE TRANSFER

Knowledge transfer from expert using positive and negative examples.
INDISCERNIBILITY FUNCTION

\[ N(x) = (\inf_A)^{-1}(u) \]

\[ \text{neighborhood of } x \]

\[ x \text{IND} (A) y \iff \inf_A(x) = \inf_A(y) \]
\( \overline{B X} = \bigcup \{ Y \in U / B : Y \subseteq X \} \)

\( \underline{B X} = \bigcup \{ Y \in U / B : Y \cap X \neq 0 \} \)

\( \overline{B X} \neq \underline{B X} \) rough sets (Zdzislaw Pawlak 1982)
VAGUENESS

- Sorites (bald men) paradox, (Eubulides, ca. 400 BC)
- “Der Begriff muss scharf begrenzt sein. Einem unscharf begrenzten Begriff würde ein Bezirk entsprechen, der nicht überall ein scharfe Grenzlinie hätte, sondern stellenweise ganz verschwimmend in die Umgebung überginge”

(The concept must have a sharp boundary. To the concept without a sharp boundary there would correspond an area that had not a sharp boundary-line all around)

Gottlob Frege (1848 – 1925)

*Grundlagen der Arithmetik 2*, Verlag von Herman Phole, Jena (1893)
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

\[ x \rightarrow \text{Inf}(x) \rightarrow N(x) = \text{Inf}^{-1}(\text{Inf}(x)) \]

neighborhood of \( x \)
APPROXIMATION SPACE

\[ AS = (U, N, \nu) \]

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

\[ UPP(AS, X) = \{ x \in U : \nu(N(x), X) > 0 \} \]
EXAMPLE OF ROUGH INCLUSION
(Jan Łukasiewicz, 1913)

\[ \nu_{st}(X,Y) = \begin{cases} \frac{|X \cap Y|}{|X|} & \text{if } X \neq \emptyset \\ 1 & \text{if } X = \emptyset \end{cases} \]

\[ C \subseteq U, \; x \in U \]

\[ \nu_{st}(N(x),C) = 1 \iff N(x) \subseteq C \]

\[ \nu_{st}(N(x),C) = 0 \iff N(x) \cap C = \emptyset \]

\[ \nu_{st}(N(x),C) \neq 0 \iff N(x) \cap C \neq \emptyset \]
ROUGH 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

HOW TO ESTIMATE INCLUSION OF SUCH NEIGHBORHOOD INTO $C$ IF WE DO NOT KNOW $C$ OUTSIDE $U$?
GRANULATION OF ARGUMENTS

FOR AND AGAINST

Argument represented by

- $pat$: pattern (e.g., left hand side of decision rule, e.g., $T=\text{high} \land H=\text{Yes} \rightarrow \text{Flue} = \text{Yes}$)
- $\varepsilon_1$: degree of object inclusion to pattern
- $\varepsilon_2$: degree of pattern inclusion to the decision class
ARGUMENTS ARE USED IN CALSSIFIER CONSTRUCTION

The arguments are used by a conflict resolution strategy (fusion operation) to predict the decision, i.e., to decide if the analyzed concept belongs to a concept or not.
INDUCTION OF CLASSIFIERS

\[ \alpha_1 \rightarrow C_1 \]
\[ \alpha_2 \rightarrow C_1 \]
\[ \alpha_3 \rightarrow C_1 \]

\[ \beta_1 \rightarrow \neg C_1 \]
\[ \beta_2 \rightarrow \neg C_1 \]
\[ \beta_3 \rightarrow \neg C_1 \]
\[ \beta_4 \rightarrow \neg C_1 \]

\[ G_1 = (\alpha_1, \alpha_2, \alpha_3) \]
\[ G_2 = (\beta_1, \beta_2, \beta_3, \beta_4) \]

Match

Conflict_res

\[ ((\varepsilon_1, \varepsilon_2, \varepsilon_3), (\varepsilon_4, \varepsilon_5, \varepsilon_6, \varepsilon_7)) \]

Conflict_res (Match(x, G_1, G_2))
There are two cultures in the use of statistical modeling to reach conclusions from data. One assumes that the data are generated by a given stochastic models. The other uses algorithmic models and treats the data mechanism as unknown. The statistical community has been committed to the almost exclusive use of data models. This commitment has lead to irrelevant theory, questionable conclusions, and has kept statisticians from working on a large range of interesting current problems. ... If our goal as a field is to use data to solve problems, then we need to move away from exclusive dependence on data models and adopt a more diverse set of tools.
Inductive solutions are derived in two steps: inductive step (from particular to general) and next deductive step (from general to particular).

Transductive solutions are derived in one step, directly from particular to particular (the transductive step).
Information granularity is a concomitant of the bounded ability of sensory organs, and ultimately the brain, to resolve detail and store information.

Human perceptions are, for the most part, intrinsically imprecise.

Boundaries of perceived classes are vague.

The values of perceived attributes are granular.

Information granulation may be viewed as a human way of achieving data compression.

It plays a key role in implementation of the strategy of divide-and-conquer in human problem-solving.
LAYERED LEARNING & ONTOLOGY APPROXIMATION
_LAYERED LEARNING

a new learning approach for teams of autonomous agents acting in real-time, noisy, collaborative and adversarial environments

Given a hierarchical task decomposition, layered learning allows for learning at every level of the hierarchy, with learning at each level directly affecting learning at the next higher level.

“Layered learning in multiagent systems: A winning approach to robotic soccer”

P. Stone 2000
CONSTRUCTION OF ARGUMENTS
FOR AND AGAINST
FOR CONCEPTS ON HIGHER LEVEL
FROM ARGUMENTS ON LOWER LEVEL
OF ONTOLOGY
GRANULATION OF CONSTRUCTIONS TO LOCAL SCHEMES (PRODUCTION RULES)

Any local scheme corresponding to a local dependency between vague concepts can be considered as a family of transducers satisfying a monotonicity property with respect to the linear order of linguistic degrees.
PATTERN CONSTRUCTION
GRANULATION

\[ C_1 \geq "large" \quad C_2 \geq "small" \]

\[ C_4 \geq "medium" \]
AR-SCHEMES

- Patterns for complex objects can be expressed by AR-schemes
- AR-scheme is a multi-level tree structure
- Root: inclusion degree of constructed higher level patterns into the root concept
- Leaves: inclusion degrees of primitive patterns into the concepts corresponding to leaves

\[ C_1 \geq \text{“large”} \quad C_2 \geq \text{“small”} \]
\[ C_3 \geq \text{“large”} \quad C_4 \geq \text{“medium”} \quad C_5 \geq \text{“small”} \]
Synthesis of simple AR-scheme

C1...C5 are concepts approximated by three linearly ordered layers: small, medium, and large.
MAP OF GRANULES
FROM NEIGHBORHOODS OF OBJECTS TO CLASSIFIERS, BEHAVIORAL PATTERNS AND ADAPTIVE SCHEMES
APPLICATIONS:
COMPLEX CONCEPT
APPROXIMATION
CONTROL OF AUV

UAV
Road simulator
(http://logic.mimuw.edu.pl/~bazan/simulator/)

- The board of simulation
- Vehicles as autonomous agents
- Operations and maneuvers
- Simulation of sensors
- Concepts
- Data storing
Results of experiments for concept: “Is the vehicle driving safely?”

<table>
<thead>
<tr>
<th>Decision class (YES + NO)</th>
<th>Method</th>
<th>Accuracy</th>
<th>Coverage</th>
<th>Real accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>YES</td>
<td>RS</td>
<td>0.978</td>
<td>0.946</td>
<td>0.925</td>
</tr>
<tr>
<td></td>
<td>ARS</td>
<td>0.962</td>
<td>0.992</td>
<td>0.954</td>
</tr>
<tr>
<td>NO</td>
<td>RS</td>
<td>0.633</td>
<td>0.740</td>
<td>0.468</td>
</tr>
<tr>
<td></td>
<td>ARS</td>
<td>0.862</td>
<td>0.890</td>
<td>0.767</td>
</tr>
</tbody>
</table>

Real accuracy = Accuracy * Coverage
Results of experiments for concept: “Is the vehicle driving safely?”

*Learning time and the rule set size*

<table>
<thead>
<tr>
<th>Method</th>
<th>Learning time</th>
<th>Rule set size</th>
</tr>
</thead>
<tbody>
<tr>
<td>RS</td>
<td>801 seconds</td>
<td>835</td>
</tr>
<tr>
<td>ARS</td>
<td>247 seconds</td>
<td>189 (average number of rules from all concepts)</td>
</tr>
</tbody>
</table>
COMPLEX BEHAVIORAL PATTERNS & PERCEPTION RULES FOR SELECTION RELEVANT PARTS: On-line Elimination of Non-Relevant Parts of Complex Objects in Behavioral Pattern Identification (ENP method)

J. Bazan et al (RSFDGrC 2004)
An example of behavioral graph for single vehicle

- Acceleration on the right lane
- Acceleration and changing lanes from right to left
- Deceleration on the right lane
- Stable speed on the right lane
- Stable speed and changing lanes from right to left
- Changing lanes from right to left
- Stable speed and changing lanes from left to right
- Deceleration and changing lanes from left to right
- Deceleration on the left lane
- Acceleration on the left lane
Behavioral graph for a group of objects (two vehicle of objects during overtaking)

1. Vehicle A is behind B on the right lane

2. Vehicle A is changing lanes from right to left, vehicle B is driving on the right lane

3. Vehicle A is moving back to the right lane, vehicle B is driving on the right lane

4. Vehicle A is driving on the left lane and A is passing B (B is driving on the right lane)

5. Vehicle A is changing lanes from left to right, vehicle B is driving on the right lane

6. Vehicle A is before B on the right lane
Data sets

- The experiments have been performed on the data sets obtained from the road simulator.
  - A train data set consists of 17553 objects generated by the road simulator during one thousand of simulation steps.
  - A test data set consists of 17765 objects collected during another (completely different) session with the road simulator.
- Train&test method has been performed to estimate accuracy.
## Results of experiments for the overtaking pattern

### Table

<table>
<thead>
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<th>Method</th>
<th>Accuracy</th>
<th>Coverage</th>
<th>Real accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>YES</td>
<td>RS-D</td>
<td>0.800</td>
<td>0.757</td>
<td>0.606</td>
</tr>
<tr>
<td></td>
<td>BP</td>
<td>0.923</td>
<td>1.0</td>
<td>0.923</td>
</tr>
<tr>
<td></td>
<td>BP-E</td>
<td>0.883</td>
<td>1.0</td>
<td>0.883</td>
</tr>
<tr>
<td>NO</td>
<td>RS-D</td>
<td>0.998</td>
<td>0.977</td>
<td>0.975</td>
</tr>
<tr>
<td></td>
<td>BP</td>
<td>0.993</td>
<td>1.0</td>
<td>0.993</td>
</tr>
<tr>
<td></td>
<td>BP-E</td>
<td>0.998</td>
<td>1.0</td>
<td>0.998</td>
</tr>
<tr>
<td>All classes (YES + NO)</td>
<td>RS-D</td>
<td>0.990</td>
<td>0.996</td>
<td>0.956</td>
</tr>
<tr>
<td>(YES + NO)</td>
<td>BP</td>
<td>0.989</td>
<td>1.0</td>
<td>0.989</td>
</tr>
<tr>
<td></td>
<td>BP-E</td>
<td>0.992</td>
<td>1.0</td>
<td>0.992</td>
</tr>
</tbody>
</table>

Real accuracy = Accuracy * Coverage
Reduction of the perception time in case of ENP method

(for decision class NO – no overtaking)

The average time for any pair of vehicles

The average time for near vehicles, driving in the same direction

The sequence of time windows that is given for perception of behavioral patterns
**Systems of complex objects with the following features:**

- objects are changing over time
- dependencies between objects
- cooperation between objects
- ability to perform flexible autonomous complex actions by objects

**Examples:**

- Complex dynamic system: *a given patient*
- Complex object: *a disease of the patient (e.g., respiratory failure)*
The experiments have been performed on the data sets obtained from *Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow.*

- The data were collected between 2002 and 2004.
- The detailed information about treatment of 340 newborns:
  - perinatal history, birth weight, gestational age, lab tests results, imagine techniques results, detailed diagnoses during hospitalization, procedures and medication.
The respiratory failure develops when the rate of gas exchange between the atmosphere and blood is unable to match the body's metabolic demands.

Arterial blood gas can be used to define respiratory failure – lower level of blood oxygen and accumulation of carbon dioxide.

- Clinical symptoms: increased rate of breathing, accessory respiratory muscles use, peripheral cyanosis
- Other useful procedures: X-ray lung examination, lung biopsy, bronchoalveolar lavage, echocardiography
THE RESPIRATORY FAILURE
AS A COMPLEX OBJECT

The respiratory failure

- **Sepsis**
  (generalized reaction on infection leading to multiorgan failure)

- **Ureaplasma**
  lung infection
  (acquired during pregnancy or birth)

- **RDS**
  (respiratory distress syndrome)

- **PDA**
  (patent ductus arteriosus)
MONITORING OF COMPLEX DYNAMIC SYSTEMS USING RISK PATTERNS

- **Domain knowledge** (e.g., ontology of concepts, risk pattern specification)

- **Data sets**
  - Data logging by sensors

- **Complex dynamic system** (e.g., an infant)
  - Intervention by special tools

- **Control module**

- **Classifier construction for risk patterns**

- **Perception of risk patterns**

- **Networks of classifiers**

- **System behavior view**
AN EXAMPLE OF BEHAVIORAL GRAPH
(the simple model of behavior for a single patient in sepsis)

Sepsis is not present (multi-organ failure is not detected)

Progression of multi-organ failure in sepsis on level 3

Progression of multi-organ failure in sepsis on level 4

Progression of multi-organ failure in sepsis on level 2

Progression of multi-organ failure in sepsis on level 1

Sepsis without multi-organ failure

Four possibilities of transition from the node: Sepsis without multi-organ failure
Behavioral graph as a behavioral pattern (the risk pattern of death due to respiratory failure)

- The visualization of infant behavior by a path in the behavioral graph Behavioral graph (behavioral pattern) as a classifier:
  - Path:
    - Stable and mild respiratory failure in sepsis,
    - Stable and severe respiratory failure in sepsis
    - Exacerbation of respiratory failure from mild to severe in sepsis,
      matches the graph
  - Path:
    - Stable and severe respiratory failure in sepsis,
    - Exacerbation of respiratory failure from moderate to severe in sepsis,
    - Stable and moderate respiratory failure in sepsis
      doesn’t match the graph
The experiments have been performed on the data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow.

- The data were collected between 2002 and 2004.
- The detailed information about treatment of 340 newborns:
  - perinatal history, birth weight, gestational age, lab tests results, imagine techniques results, detailed diagnoses during hospitalization, procedures and medication.

Train&test method has been performed to estimate accuracy, sensitivity and specificity.

- A train data set consists of 5810 objects and a test data set consists of 5289 objects
Results of experiments for the risk pattern of death due to respiratory failure

<table>
<thead>
<tr>
<th>Decision class</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes (the high risk of death)</td>
<td>0.992 (sensitivity)</td>
</tr>
<tr>
<td>No (the low risk of death)</td>
<td>0.936 (specificity)</td>
</tr>
<tr>
<td>All classes (Yes + No)</td>
<td>0.956 (accuracy)</td>
</tr>
</tbody>
</table>

Measures description:

- **sensitivity** - the proportion those cases having a positive test result of all positive cases tested,
- **specificity** - the proportion of true negatives of all the negative cases tested,
- **accuracy** - the ratio of the number of all properly classified cases to the total number of tested cases.
As a measure of planning success (or failure) in our experiments, we use the special classifier that can predict the similarity between two plans as a number between 0.0 and 1.0.

- This classifier has been constructed on the basis of the ontology specified by human experts and data sets.

The average similarity between plans for all tested situations was **0.82**.
THE PROBLEM OF COMPARISON OF PLANS

Plan 1: (e.g., proposed by human experts)

Plan 2: (e.g., generated automatically by our computer system)

Problem: How to compare Plan 1 and Plan 2?

Solution: A tool to estimate the similarity between plans.
An example of medical ontology to support the estimation of similarity between plans of the treatment of newborn infants with the respiratory failure

General similarity in the approach to the respiratory failure treatment

Similarity in treatment of Ureaplasma

Similarity in use of macrolide antibiotics in treatment of Ureaplasma infection

Similarity in treatment of sepsis

Similarity in treatment of RDS

Similarity of sucralfat administration

Similarity in treatment of PDA

Similarity of PDA closing procedure

Similarity of a causal treatment of sepsis

Similarity of a symptom treatment of sepsis

Similarity of antibiotics use

Similarity of anti-mycotic agents use

Similarity of corticosteroid use

Similarity of catecholamin use

Similarity of mechanical ventilation mode

Similarity of hemostatic agents use

16 concepts and 18 connections

Any concept represents different aspect of similarity between medical plans
UNDERSTANDING DOMAIN KNOWLEDGE

CONCEPT APPROXIMATION USING ROUGH MEREOLGY
HARD SAMPLES
Figure 6. The concept hierarchy for sunspot classification problem
Figure 7. Left: the classification accuracy of standard and layered method for some concepts in the ontology presented in Fig. 6. Right: the classification accuracy of standard and layered method for particular decision classes.
ALICE II PROJECT
ALICE II LINE-CRAWLING ROBOT
$d(x) = 1 \Leftrightarrow \text{behavior } x \text{ is accepted by the system}$
REINFORCEMENT LEARNING

**Episode**

\[
\begin{bmatrix}
  r_{t-n-1} & \cdots & r_{t-i-1} & \cdots & r_{t-2} & \cdots & r_{t-1} \\
  a_{c_{t-n}} & \cdots & a_{c_{t-i}} & \cdots & a_{c_{t-1}} & \cdots & a_{c_t} \\
  s_{t-n} & \cdots & s_{t-i} & \cdots & s_{t-1} & \cdots & s_t
\end{bmatrix}
\]

- **Rewards**
- **Actions**
- **States**

**B-lower approximation of** \( D = \{x \in U : d(x) = 1\} \)

\[ \nu_i = \nu(B_{ac}(x_{t-i}), B_*(D)) \]

**All B-indiscernible situations with** \( x_{t-i} \) **with action** \( ac = a_{c_{t-i}} \)

\[
\bar{r}_{ac,t} = \frac{1}{n} \sum_{i=1}^{n} \nu_i; \quad \bar{W}_{ac,t} = \frac{1}{n} \sum_{i=1}^{n} \bar{r}_{ac,t-i}
\]

**Q**\((s_i, ac)\) = \[
\sum_{i=1}^{n} \frac{\bar{r}_{ac,t-i}}{\bar{W}_{ac,t-i}} \left[ R_{ac,t-i} - Q(s_{t-i}, ac) \right]
\]

**The sum of rewards for** \( ac \) **in the episode ending at** \( t-i \)
REINFORCEMENT LEARNING

- REINFORCEMENT LEARNING = learning of complex concept making it possible to estimate the degree of $Q(s_t, a_c)$
- Domain knowledge: explanations of arguments for and against performing a given action in a given situation
Organization of cortex – for instance visual cortex – is strongly hierarchical.

Hierarchical learning systems show superior performance in several engineering applications.

This is just one of several possible connections, still to be characterized, between learning theory and the ultimate problem in natural science – the organization and the principles of higher brain functions.

NUEROSCIENCE: T. Poggio, S. Smale Notices AMS, Vol.50, May 2003
ONTOLOGY LEARNING

- Strategies for learning a relevant ontology for solving problems from a given (small) class of problems
NEW GRANULES

WISDOM GRANULES
Wistech

Knowledge Management Technology

Information Technology

Database Technology

TECHNOLOGY LEVELS

TECHNOLOGY HIERARCHY

THREE COMPLEXITY LEVELS OF THE SOLUTION PROBLEM SUPPORT

data = information + interpretation

information = data + interpretation

knowledge = information + information relationships + inference rules

wisdom = knowledge sources network + adaptive judgment + interactive processes
WISDOM = RIGHTLY JUDGING

- WISDOM - inference engine interacting with real-life environment which is able to identify important problems, find for them satisfactory solutions having in mind real-life constraints, available knowledge sources, and personal experience
WISDOM EQUATION

wisdom =

knowledge sources network +

adaptive judgement +

interactive processes
The main objective of **Wistech** is to automate support for the process leading to wise actions.

These activities cover all areas of man’s activities, from the economy, through medicine, education, research, development etc.

In this context, one can clearly see how large a role in the future may be played by advancing Wistech.
WISTECH: RGC for APPROXIMATE REASONING in MAS

- Learning ontology
- Knowledge representation issues
- Selection knowledge relevant for problem solving from knowledge networks
- Approximation of concepts representing intentions, desires, beliefs, social patterns, ...
- Reasoning about changes
- Negotiation, conflict resolution
- Planning
- Cooperation
- Adaptation
- Interaction
- Autonomy computing
- ...
ONTOMETRY APPROXIMATION IN DISTRIBUTED ENVIRONMENTS: TOWARD PERCEPTION LOGIC
PERCEPTION LOGIC

A system of LOCAL LOGICs interacting by using constrained sums performed on approximation spaces for achieving the goals.

- Family of approximation spaces for a local ontology of concepts

- Approximation spaces relevant for:
  - Discovery of interesting patterns and dependencies
  - Granulation of patterns to new concepts
PERCEPTION LOGIC

- Perception Logic: a system of local logics interacting and evolving in time based on calculi of approximation spaces
- Local Logics + Interactions + reasoning about changes
- Local Logics:
  - over ontology of concepts
  - ontology is approximated in a hierarchical way starting from sensory concepts
- Interactions modelled by constrained sums:
  - new approximation spaces, new concepts and dependencies, new local logics
  - evolutionary strategies for discovery of relevant interaction and local logics (MAS: negotiations, conflict resolution, coalition formation,...)
- Tools for reasoning about such systems
Developing Wistech under a Wistech Network (WN) co-operating with one another in accordance with open principles based on Open Innovation Principles

<table>
<thead>
<tr>
<th>Phase/Product</th>
<th>Summary</th>
<th>Spider</th>
<th>Conceptual Clustering</th>
<th>Wisdom Extraction</th>
<th>Wisdom Assistant</th>
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<td>Brand Monitoring Summary</td>
<td>Brand Monitoring Spider</td>
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<td>Lawyer Summary</td>
<td>Lawyer Spider</td>
<td>Lawyer Conceptual Clustering</td>
<td>Lawyer Wisdom Extraction</td>
<td>Lawyer Wisdom Assistant</td>
</tr>
</tbody>
</table>
SUMMARY

- The approach covers the approximation of vague concepts and dependencies specified in a given ontology.

- Our ontology is presented in the framework of information granule calculi.

- The outlined methods for hierarchical construction of patterns, classifiers and vague dependency approximation create the basic step in our project aiming at developing approximate reasoning methods in distributed systems.
SUMMARY:
TOWARD APPROXIMATE REASONING IN MAS AND CAS

- STRATEGIES FOR GENERATION AND ANALYSIS OF GRANULES ON DIFFERENT LEVELS OF HIERARCHY
  - DATA GRANULES
  - INFORMATION GRANULES
  - KNOWLEDGE GRANULES
  - WISDOM GRANULES
  - METAGRANULES FOR APPROXIMATE REASONING ABOUT GRANULES
- ...
The following comment from G.W. Leibniz on the idea to automate the processing of concepts representing thoughts should also not surprise us:

_No one else, I believe, has noticed this, because if they had ... they would have dropped everything in order to deal with it; because there is nothing greater that man could do._
CALCULI OF APPROXIMATION SPACES IN DYNAMICAL SYSTEM MODELLING

- The approximation spaces are allocated in different agents and they are used to approximate concepts, discover new concepts and the dependencies between concepts.
- The agents or their teams can interact what helps them to construct new approximation spaces more relevant for understanding of their environments (e.g., to better approximate concepts or to discover new concepts) and to select more relevant actions to achieve agent goals.
- The interactions are realized by constrained sums.
- The dynamics of such a system is based on learning by individual agents and agent teams new concepts and dependencies that are next used for performing further actions by agents or their teams.
CALCULI OF APPROXIMATION SPACES IN DYNAMICAL SYSTEM MODELLING

- A system of evolving local theories of agents belonging to the system.
- These theories, are changing in time as the result of interactions between agents.
- The agents are learning to select the relevant, for their goals, behavior on the basis of properties of changes in their theories and in information about satisfiability of concepts in their theories.