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AN ONTOLOGY-BASED KNOWLEDGE REPRESENTATION TOWARDS SOLVING BONGARD PROBLEMS

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Abstract. *Flexible logical reasoning is a necessary ability for humans living in a society, which involves implicit knowledge and common sense that are usually unshown. As a formal problem of context-dependent problems, Bongard problems (BPs) were proposed by M. M. Bongard in the mid-1960s as the benchmark test to evaluate the intelligent level of humans/machines to focus on how a unique minimum set can be found to satisfy necessary and sufficient conditions to discriminate two given figure groups. In consideration of artificial intelligences to solve BPs, we proposed the way to introducing semantic web tools including resource description framework (RDF) as the transparent logical reasoning process and hypothesized that BPs can be solved in the framework of Web Ontology Language (OWL) with the form of RDF triples, i.e., subject-predicate-object expressions, and the pellet incremental reasoner. According to this methodology, object and data properties were employed as a small set of OWLs to find the critical relationship to solve a specific BP, for example, IsParallelTo, IsPerpendicularTo were object properties and HasLength 4.0mm as data property and then an RDF triple was given as < Line1, IsParallelTo, Line2> for a part of the solution of BP #39 which is solved by rules of parallel lines v.s. non-parallel lines. This study hence holds a prominent position in exploring the modeling of logical reasoning processes in the human intelligence as opposed to probabilistic approaches in artificial intelligences (AIs), highlighted in the recent trend.*
Keywords: Ontology, Bongard problem, Pattern recognition, Cognition, Analogy making, Metadata

1. **Introduction.** Even infinite number of possible options are abound in front, the human intelligence can focus on possible and vital options for making a decision, to avoid the Frame Problem that McCarthy and Hayes formulated in 1969 [1]. The ability on multi-dimensional problem-solving is a clue for providing an intelligent machine equivalent to our intelligent level in the case of context-dependent problems, or ill-posed problems, and it requires the machine to solve following issues as primitive functions.

1) Problem-solving ability in bounded time,
2) Abilities to select a minimum set of clues to solve the target problem and compensate lacks of information depending on circumstances in ill-posed problems,
3) Integration of past and present knowledge and the accumulation into a consistent internal (knowledge) model for providing intelligent behavior (selection),

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4) Understanding of analogies that we usually use in perception and action naturally [2,3], which can be built by probabilistic approaches [4].

In this study, we focused on the second and third issues through the exploration of a solver of BPs. There are studies focusing on semantics to solve games [5-12]; however, those are mostly in case studies. A systematic treatment by using the mathematical formulation of the solver and the implementation into a standard logic description is crucial for the elucidation of internal mechanisms of the brain to solve the problem.

2. **Bongard Problems.** There are similarities of logical reasoning processes in games such as Chess, and Go [5,6], in the sense of recursive searching on all the possibilities from the current situation, which may cause a combinatory explosion but it is restricted by constraints by rules and player's strategy [6], as illustrated in Figure 1. In a formal way to simplifying the games, BPs consistently have nearly infinite infeasible possibilities to find the unique and minimum necessary and sufficient conditions to solve the puzzle.

BPs were currently proposed as a set of 100 puzzles by Russian computer scientist M. M. Bongard [7], focusing on visual perception, categorization, and recognition [7-9]. As shown in Figure 2, each problem consists of a total of 12 boxes with a lump of six boxes on the left side and another lump on the right side [8]. The goal of a player is to focus on a rule for respective sides and guess a major difference between both the given lumps (without considering the absolute position of each box). The difference between each side varies from perceptual features [7-9] (like – outlined figure, filled figure, large, small, open structure, closed structure, and area), elementary relationships (like: above, below, on left, and on right) or even numerosity (like: number of lines, number of dots, and number of intersections) [8,9]. There exists a unique set of conditions to differentiate two figure groups on either side [7-9].

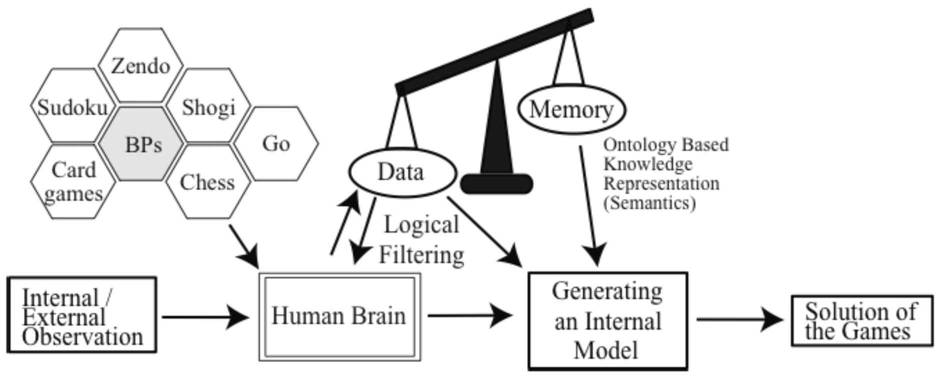

Figure 1. Human brain utilizes logic and semantics for solving games.

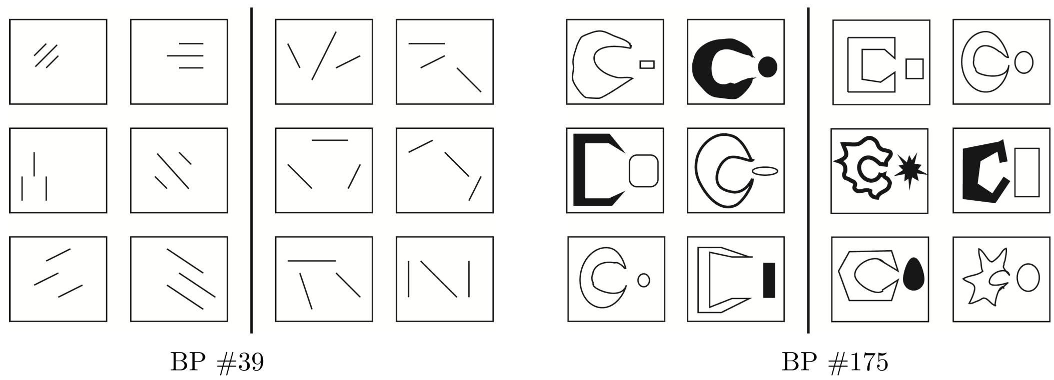

Figure 2. Examples of Bongard problems (schematically re-illustrated from originals [8])

In consideration of the BP #175 (Figure 2, right), the issue is not only restricted in a simple comparison of features between right and left groups but also relationships on both sides. In this case, figures are very similar, while the condition of whether or not the small object can pass through a gap existing in the large object for entering inside is different. This logical expression of "meaning" is the essence of BP solutions [9].

Foundalis [8] developed a two-layer cognitive architecture, named Phaeaco, using multiple codelets, (small independent pieces of codes) [7,8]. The first layer named as retinal level architecture and second layer named as cognitive level architecture worked in a pipeline fashion [7,8]. This approach solved a limited number of BPs and faced difficulty in treatments of complex meaning defined by a combination, hierarchical structure and recursive operation of primitive items. Therefore, further theoretical advancement is expected to treat following issues.

- Explicit rules to judge information as necessary or unnecessary,
- Inclusion of a standard meta-data description [13,14],
- Discrimination of contents from background [8,9].

This paper is organized as follows. Section 2 provides an introduction to the Bongard problems and major challenges faced in solving them. Description about ontology and its implementation using Protégé [15] are discussed in Sections 3 and 4. The outcomes and the conclusion for this approach are provided in Sections 5 and 6 respectively.

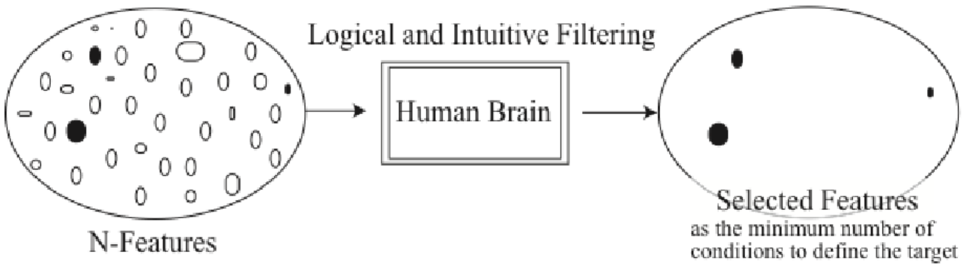

Figure 3. Generalized complexity due to N-features obtained from any given BP

3. **Problem Definition.** In the BP, individual figure potentially has an infinite number of properties $P = \{P_1, P_2, \ldots, P_n, \ldots\}$ because a new property can be generated by new combination and a new relationship between pre-existing properties. In this puzzle, the only restriction is to determine individual property sets to discriminate figure groups in the left and right sides without any overlap logically. Therefore, a BP solver is equivalent to a searching method of a minimum set of properties to classify two groups, as illustrated in Figure 3. However, the conventional formulation to find the two property sets from all possible discrete combinations easily meets the combinatory explosion problem and takes infinite time to obtain the solution at last. Therefore, an effective treatment is to transform from the discrete combination problem to a continuous optimization problem. Suppose a state space can be spanned by axes with measures of selected properties, like a round-or-edged axis to represent how edges may exist in a figure component, each box is plotted as a point in the state space, and then an appropriate subspace to include the points for left and right sides, which are described as S_A and S_B, and then two regions of S_A and S_B in the state space are isolated each other, which denotes $S_A \cap S_B = \Phi$.

With respect to indexing as S_A and S_B for six boxes on left and right sides, individual figure boxes are indexed from L_1 to L_6 and from R_1 to R_6 respectively. In the state space, each box can be represented as the point x in a multidimensional state space with properties $P = (P_1, P_2, \ldots, P_n, \ldots)$ as described as

$$x^{L1} = \left(x_1^{L1}, x_2^{L1}, \ldots, x_n^{L1}, \ldots\right)$$

$$x^{R1} = \left(x_1^{R1}, x_2^{R1}, \ldots, x_n^{R1}, \ldots\right)$$

where

$$\textit{Properties}\left(x^{L1}\right) = \left(\{\textit{independent properties}\}_{\text{objects}}, \{\textit{dependent properties}\}_{\text{within objects}}\right)_{L1}$$

$$\textit{Properties}\left(x^{R1}\right) = \left(\{\textit{independent properties}\}_{\text{objects}}, \{\textit{dependent properties}\}_{\text{within objects}}\right)_{R1}.$$

Independent and dependent properties denote respectively primitive properties to be determined independently such as circle, and line and relational properties to be determined by relations with other objects such as small/large, and close/far.

For example,

$$x^{R1} = (\textit{circle, number of lines, their orientations, } \ldots, \textit{ how close multiple objects, } \ldots).$$

Thus, circle and triangle objects can be written as a combination of semantics properties and points in the state space in different positions,

$$\textit{Circle} = (\textit{Rounded, Size, Texture, Color} \ldots \ \textit{smaller than} \ldots, \textit{ to the right of} \ldots),$$
$$\textit{Triangle} = (\textit{Edged, Size, Texture, Color} \ldots \ \textit{bigger than} \ldots, \textit{ to the left of} \ldots).$$

4. **Implementation.** Here we focused on the implementation part of BPs into a standard logical expression such as a machine-readable and understandable format. Efforts have been made to study knowledge representation in the artificial intelligence [11-14], called Semantic Web. The present study introduces following tools.

- RDF (Resource description framework): consisting of the vocabulary
- OWL (Ontology web rule language): containing the restriction
- The Semantic Web Rule Language (SWRL): rules for actions in the logical reasoning
- SPARQL: a query language to retrieve and manipulate the data stored in RDF.

We hypothesized that the logical description part of BPs can be described by using ontological data representation. Each RDF vocabulary representation was generated based on Protégé API [15], for class and literals. Sets of RDF triples, constituting an OWL data, are considered as a long-term memory (LTM) and a set of SWRL is a decision maker according to the logic. SPARQL acts accessibility to LTM written by RDF formats.

Table 1. Algorithm 1: SWRL framework for features in BP #39

$$F_{SA} = \textit{features}\ (\textit{Side A}\ \{L_{A1}, L_{A2}, \ldots, L_{Ai}\})$$
$$F_{SB} = \textit{features}\ (\textit{Side B}\ \{L_{B1}, L_{B2}, \ldots, L_{Bj}\})$$
$$F_{SA} \cap F_{SB} = \Phi$$
$$S_A = \{iL_A | i \in N \wedge L_A \in F\}$$
$$S_B = \{jL_B | j \in N \wedge L_B \in F\}$$
$$S_B = F(\{L_A\}) = \begin{cases} \textit{has Parallel lines} \quad (\textit{slope}(\forall L_{A1})) = \ldots (\textit{slope}(\forall L_{Ai})) \\ \ldots \end{cases}$$
$$S_B = F(\{L_B\}) = \begin{cases} \textit{Not Parallel lines} \quad (\textit{slope}(\forall L_{B1})) \neq \ldots (\textit{slope}(\forall L_{Bi})) \\ \ldots \end{cases}$$

As a preliminary result, BP #39 (shown in Figure 2 (left)) was treated by our proposed scheme. For S_A as a set of boxes on left and S_B as a set of boxes on the right side, as shown in Algorithm 1, let L_1, L_2, $\ldots$, L_N be lines detected from the given problem. Let us consider L_{A1}, L_{A2}, $\ldots$, L_{Ai} and L_{B1}, L_{B2}, $\ldots$, L_{Bj} as lines on individual boxes of Side A and Side B. The slope feature ($\textit{slope}(\forall L)$) of each instance on either side is used to make the inference for classification as parallel lines and perpendicular lines. If slope

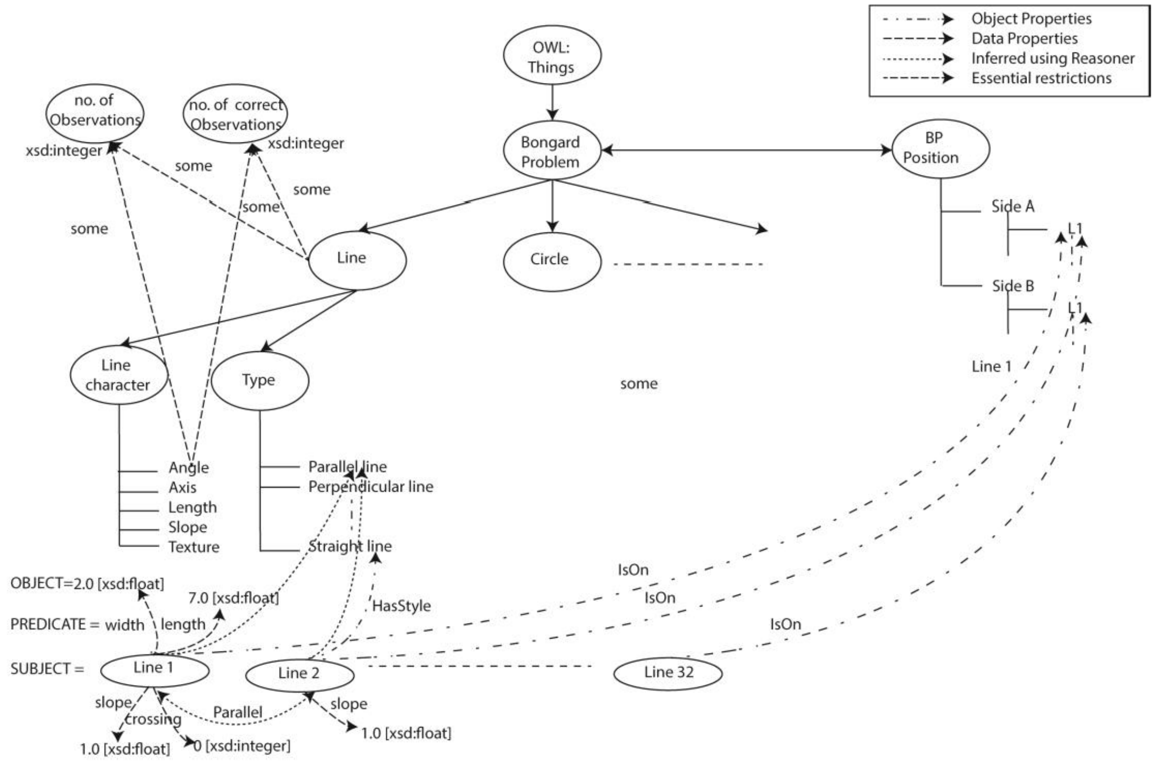

FIGURE 4. Logical structure and reasoning flow of the given line ontology

values of all the instances (for i lines on Side A and j lines on Side B) in a given lump is the same, it is inferred to be an instance of class parallel lines.

From the list of defined data properties and object properties, the SWRL rules are used to detect lines, which fall into two categories such as "parallel lines" and "not parallel lines" respectively. The rules can be mathematically interpreted as shown in Algorithm 1. Using Protégé API the "line ontology", to solve BP #39, was generated using multiple classes (instant domains), properties (relationships), instances (individuals) and conditions (domain and range values) (Figure 4). In this analysis, five SWRL rules were executed to detect that the lines on Side A are parallel to each other while the lines on Side B are not parallel to each other. Figure 4 represents the hierarchy of the classes and instances with their respective data and object properties from the line ontology. Each data and object property has a bounded range, provided using domain and range values.

5. **Result.** In this research, an ontology-based approach was used to make the machine solve the given Bongard problem (BP #39). Protégé ontology editor was used to develop the ontology. The OWL file is opened in Protégé API and pellet based reasoning is carried out based on the SWRL rules for the knowledge inferences. These following SWRL rules (Table 2) were used to detect the existence of parallel lines on a given side in BP #39 by evaluating the relationship between each instance.

The inferred XML representation by using RDF stream as OWL file was used and the description consists of the Uniform Resource Identifier (URI), which are resources and temporary locations where the data is preserved. For example, for class Lines, as a subclass of Type of Object, there exist subclass perpendicular lines with a property of restricted angle in the range of 89.0 to 91.0 as float value ($89.0° \leq \Phi \leq 91.0°$).

$$hasAngle\ exactly\ 1\ xsd{:}float[>= 89.0f,\ <= 91.0f] \tag{1}$$

Here the relationship between each instance, as Line1, Line2 and Line3 is represented as an RDF data as triples. Combination of multiple RDF data gives rise to an OWL, which

TABLE 2. SWRL list to represent relationships of features in BP #39

lineOntology:Line(?a) *^lineOntology:Line(?b)* *^lineOntology:HasSlope(?a,?s1)* *^lineOntology:HasSlope(?b,?s2)* *^swrlb:equal(?s1,?s2)* *^lineOntology:LiesOn(?a,?S1)* *^lineOntology:LiesOn(?b,?S1)*	$\longrightarrow$	*lineOntology:IsParallelTo(?a, ?b)*
lineOntology:IsParallelTo(?a,?b)	$\longrightarrow$	*lineOntology:ParallelLines(?a)* *^lineOntology:ParallelLines(?b)*
lineOntology:isNotParallelTo(?a,?b)	$\longrightarrow$	*lineOntology:NotParallelLines(?a)* *^lineOntology:NotParallelLines(?b)*
lineOntology:ParallelLines(?a) *^lineOntology:NotParallelLines(?a)* *^lineOntology:Line(?a)*	$\longrightarrow$	*lineOntology:NotParallelLines*

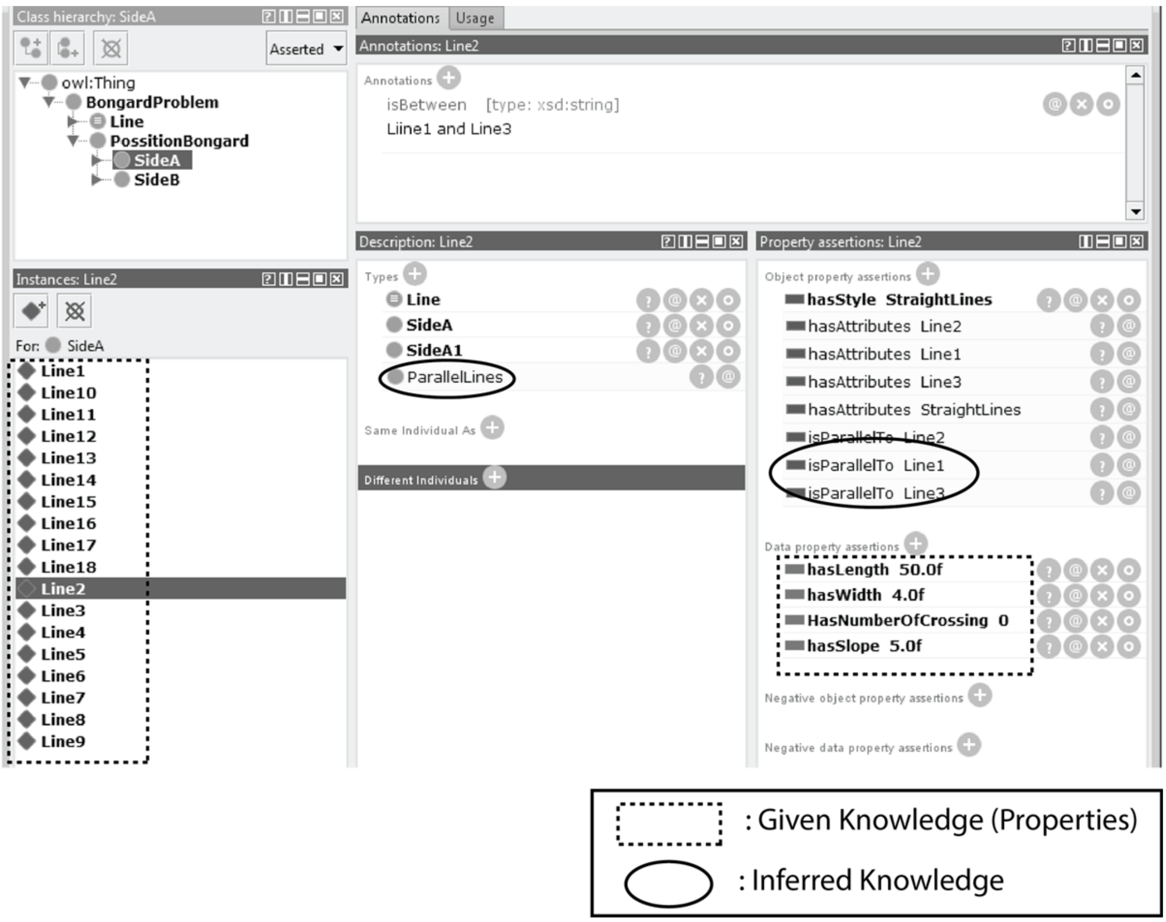

FIGURE 5. Protégé API based inference to the RDF vocabulary of BP#39

can be further inferred using a Java-based reasoned after checking the consistency of the generated hierarchy in Protégé API (as shown in Figure 5). The literals and their data properties need to be updated from the output of the image processing block based on robust classification. Such an updation along with static SWRL rules can evaluate the relationship between each object detected in a given image. Such relational database along with proper inferences can in future lead us towards autonomously solving the analogy related tasks.

Since Bongard problem does not depend merely on the asserted or prior (existing) knowledge, a metadata description and efficient pattern matching approaches are essential to enhance the ability to solve BPs. The automatic solver of BPs has a potential to apply the proposed scheme to other applications. Therefore, this approach contributes to the existing problem of assistive technologies with using artificial intelligence and robots helping our daily life. Furthermore, it could be a clue to understand the internal mechanism of the human brain to treat decision making in actual, prompt, and critical problem-solving in the dynamic and social environment.

6. **Conclusions.** The main objective of the present study was to develop a semantic web-based approach to solve the Bongard analogy problems in the aim of transparency in the logical reasoning process and generalization of the ill-posed problem. The utilization of the RDF description in the framework of ontology as the knowledge-based representation helps to understand our reasoning process in the puzzle.

As further analyses and development of the proposed system, the actual integration with a minimization of axes (properties) in the state space, as described in Section 2, problem definition, is necessary for the completion of an automatic solver of BPs. Another important point is how the obtained knowledge was accumulated into the system consistently in the sense of the fitness for the SWRL rules. Data-driven approaches including clustering methods, machine learning, neural network models are beneficial for applying an image processing part in the primary sensory system in our proposed system and separation of subspace between two figure groups after reconfiguration of the state space to be a minimized state space and plotting individual figures on the space, while the function of the reconfiguration of the state space as continuous optimization problem cannot be replaced by the data-driven approaches simply. The present result demonstrated that the linked data approach would be useful in solving of BPs with meta-data descriptions, and then this consequence provided a large potential of multidimensional analogies with a significant relation with daily life problems that we intuitively solve from the common sense.

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