Human Abduction for Solving Puzzles to Find Logically Explicable Rules in Bongard Problems: An Ontology-based Model

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Abstract

Human intelligence relying on the brain information processing has two aspects of implicit memory and explicit memory functions. A possible hypothesis is that the human intelligence is a consequence of the fusion of those two aspects and then a question is addressed as to how the flexibility of making a frame of thinking depending on the context is reconstructed by the fusion. In the assumption that an autonomous classifier provides primitive labels indicating parts in a picture and a generalizer to represent the whole in an abstract way, the problem that remains unsolved is how semantic information can be coordinated to reach the conclusion to connect parts and the whole. Bongard problems question such an issue in the form of logical picture puzzles to request to seek the unique minimum description of pictures to discriminate two groups, throughout an abductive reasoning. In the present study, we introduced methods of the semantic web technology to treat a hierarchical semantic information arisen in the abduction and the logical reasoning to obtain the conclusion and then proposed a computational model for solving the problems by using an architecture of hierarchical abductions. Possible combinations of primitive descriptions like 'circle in a triangle' is arisen as a test hypothesis to represent them commonly and then it is verified whether it matches all pictures totally in each group. The tested hypotheses from two groups are compared and it will be the solution if there are logically different, such as 'circle in a triangle' v.s. 'triangle in a circle.' Our computer experiment showed that ten selected Bongard problems were solved in the proposed framework. It indicates that the semantic information coordinator works well to solve a type of the frame problem, by coupling with autonomous classifier and generalizer. The framework may contribute to the design of the general artificial intelligence in part, especially on coordination against autonomy in semantics.

1 Introduction

Recently, multi-layer neural network models and machine learning approaches for computer vision and the first-order symbol grounding or automatic meta-labeling in the language processing accompanied with massive digital data with an amount of computer hardware performances have made prominent progress in mimicking a part of abilities of humans [Hernández-Orallo *et al.*, 2016; Taniguchi, 2017], which are called Artificial Intelligence technologies or 'AIs' simply and highlighted as 'technological singularity' [Kurzweil, 2014]. It sometimes exceeds human abilities related to the memory capacity and information processing speed as is demonstrated in human-machine matches of board games [Silver *et al.*, 2016]. However, the realization of mechanisms to reproduce higher-level abilities remains unsolved, such as sharing human values with respect to emotional reactions [Ledoux, 1998], understanding human intentions and semantics in communication without explicit background information [Minsky, 1986] and adaptivity/flexibility of making an arbitral frame of thinking to solve the facing problem depending on individual 'situation,' known as 'frame problem' [McCarthy and Hayes, 1969; Shanahan, 2016]. Those abilities are autonomously emerged in the human brain and therefore the generality and autonomy in AIs beyond conventional machine learning schemes are highly expected [Pfeifer and Bongard, 2007]. In consideration of semantics in higher cognitive functions, a systematic progression can be recognized based on the theoretical advancement of the symbol logic and its implementation in the form of the semantic web technology, with respect to AI symbolic approaches in 1970-1980 [Forbus *et al.*, 1998; Mitchell, 2003; Chen *et al.*, 2016; Johnson *et al.*, 2017].

A possible hypothesis to answer the question why the human brain is flexible and autonomous for generating an appropriate frame of thinking is that it is realized from an integration of different types of computations, which are briefly classified into two domains related to implicit memory and explicit memory. In the former one, the procedural memory, for example, is maintained the basal ganglia and related brain regions, which is considered to be reproduced by the reinforcement learning scheme, while the human has no awareness of what is going on in the learning process but posses abilities to discriminate what it is as an automatic classifier and to take the best action to maximize the benefit, which

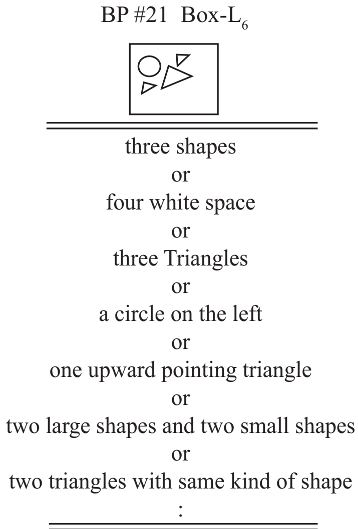


Figure 1: An example of the picture in a BP, which is represented by redundant and polysemic representations in word, as D. R. Hofstadter discussed in his book [Hofstadter, 1979].

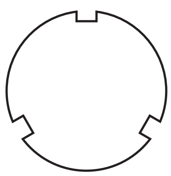


Figure 2: 'A kind of circle', or 'circular shape with notches.' An abstraction and then it becomes a simple representation.

can be formulated by the Markov process. In contrast, the latter function is associated with human consciousness. The mechanism of how the consciousness emerges in the brain is still an unreached problem, or mystery, in spite of our tremendous efforts of integrative research fields, while there are significant ambitions in constructive and embodiment approaches to build it artificially. In the present study, the working hypothesis is addressed that the flexibility of making a frame of thinking depending on the context is reconstructed by the fusion of implicit and explicit memory functions, as the basement assumption, and then it allows us to focus on a conscious process of how the brain simply represents what happen in the world, *i.e.* analogy by words. In particular, the logical reasoning process in such representations can be considered as a dynamic process from the low-level meta-label generation to semantics observed in the higher cognitive functions [McCarthy and Hayes, 1969; Forbus *et al.*, 1998; Mitchell, 2003; Chen *et al.*, 2016; Johnson *et al.*, 2017]. According to the advancement of semantic web approaches, semantic information and its relevance to the brain information processing can be discussed in the framework of computational models based on the theory of logic.

In the assumption of a high-quality visual processing will be treated appropriately by algorithms based on probabilistic models, *i.e.* machine learning scheme, the target problem will be addressed as a dynamic association among possible items to represent what it is in a minimum way and to maximize the fitness for requirements in the context. As shown in Fig.1, there are multiple ways to represent what the picture is, which is consisted of redundant and polysemic representation in words [Hofstadter, 1979] (Fig.2). The question arises what is the best representation in the current context and how we can solve the problem. According to the issue, Hofstadter introduced Bongard problems in his book [Hofstadter, 1979] as a benchmark to test an intelligent level of the agent, in the form of the logical picture puzzle. The puzzle requires a coupling between meta-cognition and logical reasoning for providing a higher level of analogy like human naturally do and it was originally proposed by Mikhail M. Bongard [Bongard, 1970]. In this problem, three core architectures are considered to cooperate together, 1) an auto-generative system to represent characteristics in the target picture with primitive forms (autonomous label generator), 2) a semantic network coordinator to find an appropriate representation without redundancy (coordinator/evaluator), and 3) an analogy maker to bind a set of the characteristics and to set a consistent representation in a simple form by ignoring unnecessary parts to conclude (generalizer) as illustrated in Fig.2. In other words, autonomy and generality are not enough for designing an intelligent agent to solve the Bongard problems and then the architecture design will be completed to add a complementary architecture as the semantic network coordinator to mediate two systems.

The article was organized following sections. Section 2 provides an overview of the Bongard problems and referred related past studies. Our theoretical framework based on the

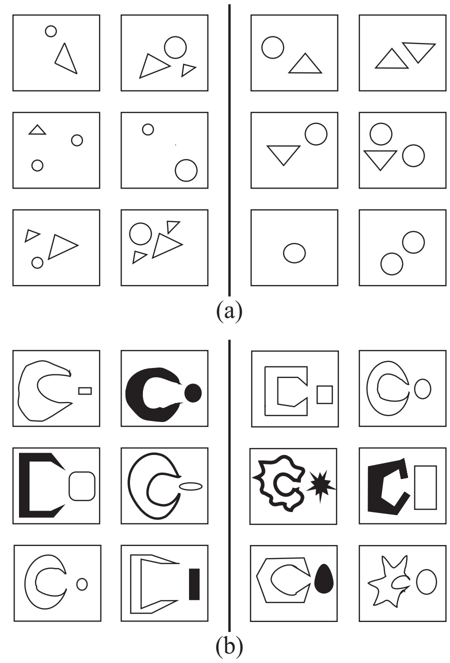


Figure 3: (a) BP #21 Small figures versus large figures; (b) BP #175 small objects can glide through the orifice versus small objects cannot glide through the orifice

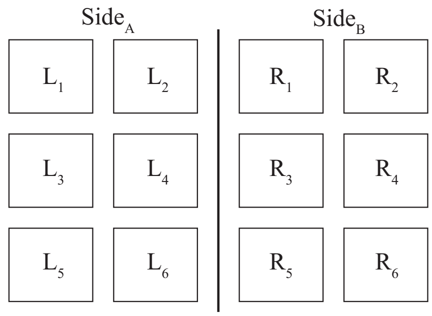


Figure 4: General indexing of a Bongard Problem

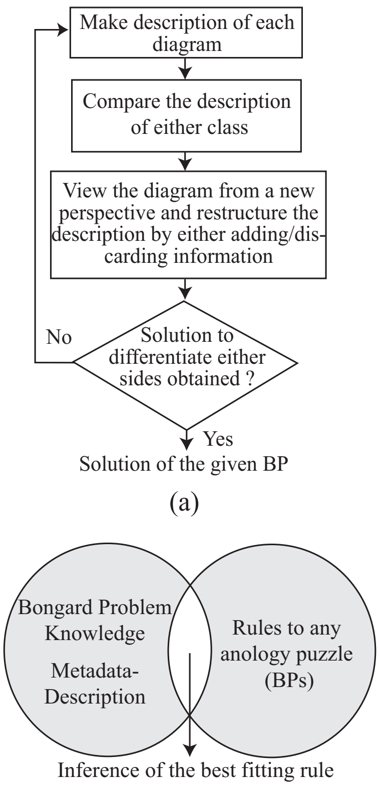
semantic web technology was introduced in Section 3. Section 3.1 briefly explained about data format and rule description for the logical reasoning and the implementation design specifically for the Bongard problems was discussed in Section 3.2. Section 4 demonstrated results of the proposed system that solved 10 selected Bongard problems. Finally, in Section 5, we discussed the obtained results and the future scope of the present approach.

2 Problem Definition

Bongard problems (BPs) are a set of 100 visual puzzles introduced in the mid-1960s by the Russian scientist Mikhail Moiseevich Bongard in his book *Pattern Recognition* [Bongard, 1970] (Fig.3). This set of two-dimensional graphical puzzles involves pattern recognition, categorization, and logical decision-making tasks to infer the similarity and dissimilarity that govern them. Every BP inherits the quality of universality of unique solutions. Although BPs are an excellent means to validate the interaction of human vision and cognitive abilities, they impose tremendous challenges in the field of AI in mimicking human logical thinking abilities.

A BP consists of 12 boxes, with a lump of six boxes on the left side and another lump of six boxes on the right side. The goal of a BP player is to find contradictory rules to logically discriminate the two given lumps, which means that the rule applicable on one side of the BP will not hold true for the other side. The BP solution is unique and obtained from predictive logical inferences in a ill-posed problem. As shown in Fig.3, the solution varies from a combination of primitive graphical features (such as texture and shape) to the spatial relationship (such as within, below, and above), numeric count (such as number of intersections and number of objects) and further abstractions (Fig.2). At primitive BPs, the logical inference starts from to consider about the similarity and dissimilarity and flexible abductions are required in cases with a higher level of analogy. In the inference process, an autonomous generation of representations is considered in a framework of the solver as a systematic recursive way of thinking as shown in Fig.3(b) to reproduce meta-cognition or the context-based description (Fig.5).

Six boxes of the BP is separated by a line as left and right sides. For the mathematical formulation, each side in a given BP is indexed as L_i and R_i $(i = 1, \cdots, 6)$ (Fig.4). As shown in Fig.1, each box holds potentially a potentially infinite num-



(b)

Figure 5: (a) Reformulated process of Hofstadter's idea to solve BP ([Hofstadter, 1979]); (b) An overview of solution to a BP

ber of properties per feature, and the interrelations between each preexisting property also lead to a new set of dependent properties, as analogy. Thus, if it is possible to reproduce a BP solver artificially, the system can be considered to to mimic the human decision-making ability in ill-posed problems, by the performance to find a simplest representation from an infinite number of possible combinations in a form of the set of properties.

If a problem is in BPs, there exist two sets to be determined by contradictory rules each other. Therefore, if $\mathbf{S}_A$ and $\mathbf{S}_B$ are assumed to be the sets, every picture in left boxes is a element of $\mathbf{S}_A$ and every picture in right boxes is a element of $\mathbf{S}_B$ and then there is no overlap, which is formulated as

$$\begin{aligned} &\mathbf{S}_A \cap \mathbf{S}_B = \emptyset \\ &\text{s.t.} \quad L_i \in \mathbf{S}_A,\ R_i \in \mathbf{S}_B\ (i = 1, \cdots, 6). \end{aligned} \tag{1}$$

For example, in the case of Fig.3(a), if rules are given as *'there exist a triangle'* and *'the number of circles is larger than one'* as a first abduction, the result is $L_i \in \mathbf{S}_A$ $(i = \{1, 2, 3, 5, 6\})$, $R_i \in \mathbf{S}_A$ $(i = \{1, 2, 3, 4\})$, $L_i \in \mathbf{S}_B$ $(i = \{3, 4\})$, $R_i \in \mathbf{S}_B$ $(i = \{4, 6\})$ and $L_4 \notin \mathbf{S}_A \wedge L_4 \notin \mathbf{S}_B$. Thus, it does not satisfy Eq.1. In the second abduction, if rules are given as *'there exist shapes with different sizes'* and *'the shape size is consistent at all'*, the result becomes much better as $L_i \in \mathbf{S}_A$ $(i = \{1, 2, 4, 5, 6\})$, $R_i \in \mathbf{S}_B$ $(i =$

$\{1,2,3,4,5,6\}$) and $L_3 \notin \mathbf{S}_A \wedge L_3 \in \mathbf{S}_B$; however the performance of the logic puzzle is not evaluated according to the error rate numerically and then it is clearly rejected as the BP solution. Finally, the solution is obtained as *'there exist a small shape'* and *'there are no small shapes'* under the complementary assumption of *'small means that the largest length of sides, or diameter, is smaller than one-fifth of the base length of the picture area'* as a hidden knowledge. The solution satisfies Eq.1 without any exception.

The fact implies that the BPs require relative information (dependent properties) to solve. These relationships can be described as follows:

$$\mathbf{x}^{\mathbf{L1}} = (x_1^{L1}, x_2^{L1} ...., x_n^{L1}, ...) \tag{2}$$

$$\mathbf{x}^{\mathbf{R1}} = (x_1^{R1}, x_2^{R1} ...., x_n^{R1}, ...) \tag{3}$$

where

$$Properties(x^{L1}) = (IP_{objects}, DP_{within\_objects})_{L1} \tag{4}$$

$$Properties(x^{R1}) = (IP_{objects}, DP_{within\_objects})_{R1} \tag{5}$$

Each box in a given BP have multiple object instances (Eq.2 and Eq.3) to solve. In principle, every picture of the box can not only has an infinite set of independent properties (IP) to represent how the picture is categorized, such as circle or triangle (as characteristics of the object) but also has dependent properties (DP) as determined by relations with other objects such as smaller/larger, close/far and left/right and so on. In the consideration of the properties in Fig.3 (a), the box R_2 can be described as follows:

$$\mathbf{x}^{\mathbf{R2}} = (Line, Circle, Triangle, ...) \tag{6}$$

$$\begin{aligned} &properties(Circle) = \\ &((Rounded, ..{}_{independent}), (leftOf, ..{}_{dependent})) \end{aligned} \tag{7}$$

It is because that *'triangle'* can be decomposed of three lines. In the same way, in the process of the abstraction, or simplification, Fig.3 (b) requires to think us *'orifice'* by ignoring difference in color, shape (rounded or edged) and detail textures. Since possible BP solution are distributed in infinite numbers of axes, it is difficult to find the solution by using random search algorithms targeting spaces with a fixed number of axes. To reach the solution in a finite time, a gradual increase of the number of properties for the combination (search space expansion) is required and associated with a contraction of space dimension by abstraction (search space contraction) as a optimization problem. In the present study, we hypothesized that the property management for controlling the space dimension and the logic rule implementation are well organized in an ontology-based approach as a BP solver.

For the sake of simplification, we assumed that the image segmentation and feature extraction are automatically processed prior to the proposed system and then this study focused on the rule generation and evaluation process with respect to the judgement as Eq.1. It highlights the importance

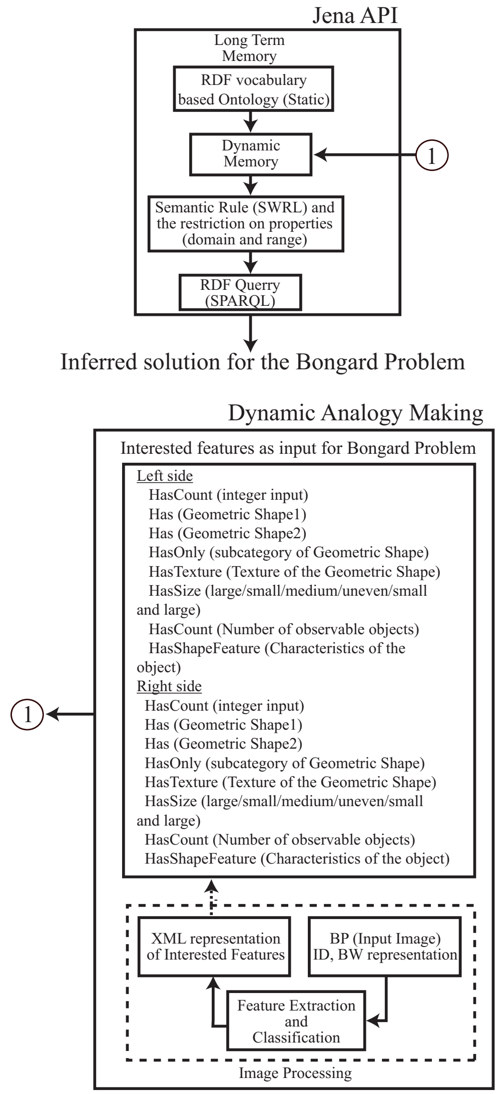


Figure 6: Proposed three level hierarchical model as the BP solver.

of effective knowledge representation for making logical inferences for solvers of BPs.

3 Proposed Framework for Solving BPs

3.1 Ontology-based scheme for knowledge representation

Each box, on either side, of a given BP holds a potentially infinite number of independent and dependent properties. To enable the machine to understand this massive amount of raw data obtained from a BP, we need a semantic knowledge representation of the raw concepts and their flexible relationships.

Ontologies can represent the knowledge in an organized and machine-understandable format with concepts and relationships among the obtained data instances. For consistent modeling of data, the context descriptions are designed using

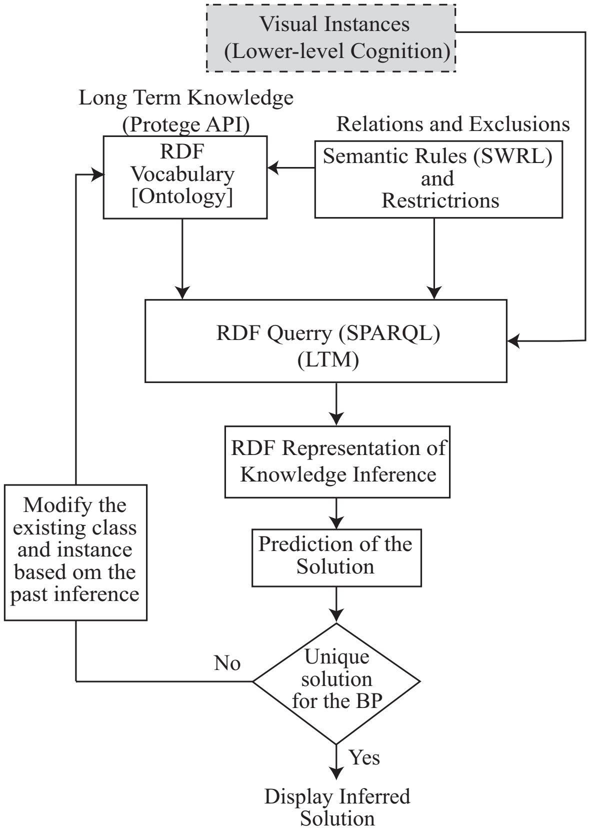


Figure 7: Our framework for solving BPs using knowledge tree

the Resource Descriptive Framework (RDF). To express rules and logical expressions for inferring the perceived visual data, Semantic Web Rule Language (SWRL) is used along with SPARQL Protocols and RDF Query Language (SPARQL). The SPARQL querying tool helps the semantic web query static RDF knowledge in a more interactive fashion. Ontologies are usually expressed as the following entities:

- Classes: These are the main instances of the domain of interest and play a vital role in defining an ontological structure (such as Web Ontology Language [OWL]: shapes; Owl: texture).
- Properties: Properties in an ontological knowledge base fall into three distinct categories, namely object properties, data properties, and annotation properties. They define the relationship-based predicates for the RDF data format (such as 'LeftOf' and 'InBetween')
- Instances: These are the subjects/predicted-individuals in the given domain (such as shape name, *i.e.* 'Circle' and 'Square').
- Rules: These are the logical statements governing the categorization and carrying out of logical inferences in the ontology.

3.2 Analysis of BPs using ontology

In his book *Gódel, Escher, Bach: An Eternal Golden Braid*, Douglas R. Hofstadter emphasized a recursive context-based approach as a possible solution to solving BPs [Hofstadter, 1979]. He discussed about the necessity of "concept networks", in which all the data are interlinked in a way that indicates their interrelations; however he did not yet complete to propose an actual solution to connect an implementation into machines. Therefore, his hypothesis on the BP solver is of interest to researchers who are interested in the limitation of the machine intelligence and the possibility of the reproduction of the human intelligence, while the process of carrying out similarity checks and funneling the inferred possible relationships between either side of the BP still remain unsolved (Fig.5).

As a first step to dig into the point of view, we proposed a way of the implementation with an ontology-based knowledge representation with large-scale interoperability and axioms, which can be easily extend for general use. As shown in Figure 6, our hypothesis verified by using a three-level hierarchical model as illustrated in Fig.6.

Table 1: Algorithm 1

Cross checking dissimilarity to detect possible solution

Step−1: *Select* $Rule_A$
  if$(Rule_A$ *satisfies* $(L_1,L_2,L_3,L_4,L_5,L_6))$
    if $(Rule_A$ *consistent in* $Side_X$ *of BP*$)$
    (Inference $->$ $Side_X$ $Predicate_X$ $Object_1)$
    else (***GOTO*** *Step−1*)
Step−2: *Select* $Rule_B$
$Rule_B$ *satisfies* $(R_1,R_2,R_3,R_4,R_5,R_6)$
    if $(Rule_B$ *consistent in* $Side_Y$ *of BP*$)$
    (Inference $->$ $Side_Y$ $Predicate_Y$ *Object2)*
    else (***GOTO*** *Step−2*)
$(Side_X$ $Predicate_A$ $Object_1)(Side_Y$ $Predicate_Y$ $Object_2)$
      if $(Object_1$ *isSameAs* $Object_2)$
      $Rule_A$ *and* $Rule_B$ *are not consistent for Left and Right sides respectively*
      else if $(Object_1$ *DifferentFrom* $Object_2)$
      $Rule_A$ *and* $Rule_B$ *is consistent for* $Side_X$ *and* $Side_Y$ *sides respectively*
      else (***GOTO*** *Step−2*)
  else (***GOTO*** *Step−1*)

In our proposed model, Static ontology is the basic knowledge structure about shapes and all the possible general knowledge of the environment. This was created to replicate the high-level cognitive state (long-term memory) of the human brain. The dynamic analogy-making block provides the visual context-based information, which varies depending on the type of BP. This block mimics the lower-level cognitive state of the human brain by providing the ontological

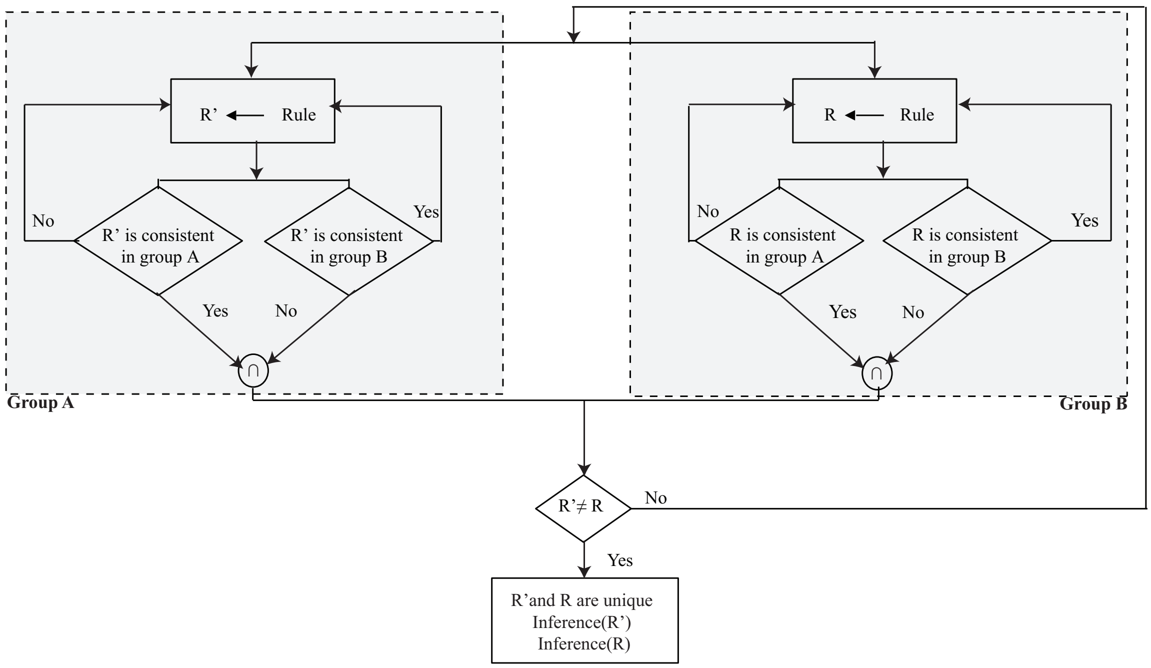


Figure 8: Cross checking dissimilarity to detect possible solution for a BP

knowledge base with instantaneous processed visual information (using Java-based graphical user interface [GUI]).

Since the complexity related to a BP increases with increases in visual instances and their properties, a meta-description (description of description) is formulated at the dynamic memory block. The logical reasoning capability and inherited knowledge about events and shapes are represented in the form of semantic rules and queries. We used the OWL reasoner based on descriptive logic for reasoning on the objects (visual instances) and their relationship in a wider perspective. As shown in Fig.6, in our approach, the inference of the best-fitting rule, as the most promising solution to a given BP, is an outcome of the logical intersection between the metadata-based description and the logical rules governing a BP. Fig.7 shows the overview of the logical decision system using the dynamic ontological knowledge base to make logical inferences governing the possible solution for a given BP. The operations carried out in our framework are as follows:

1. The visual instances are obtained from the GUI-based receivers and are imported into a static ontological knowledge base.
2. The SWRL rule reasoner is formulated in a way to create new inferred properties from the perceived instances. This rich knowledge base is then fed into the SPARQL query engine.
3. If the solution to the given BP can be formulated at this stage, the predictions are generated. Otherwise, a recursive process of inference is carried out as follows in the steps below.
4. The SPARQL query engine, along with SWRL rules, access the knowledge base to retrieve information about the instances and their respective classes. This helps in the categorizing objects and characterizing the new inferred properties.
5. The SWRL rule reasoner adds some inference based on the respective side of the BP—for example, detecting the common properties and understanding the dissimilar instances.
6. SWRL rule-based reasoning is performed on the updated knowledge base, and new inferences are made.
7. The SPARQL query retrieves all the relationships for every instance from all the 12 boxes.
8. SWRL checks for the possible solution based on the new inferred knowledge base (outcomes of the SPARQL query). If the solution to the given BP can be formulated at this stage, the predictions are outputted. The newly added inferred knowledge is removed from the static ontology-knowledge base.
9. If the solution to the given BP could not be formulated, the above-mentioned recursive process of inference is carried out again.

Here, the context-based decision-making system mainly consists of the visual instances receiver, a dynamic ontological knowledge base, logical rules, and query engines. Figure 6 represents the visual notation of the static ontological knowledge base. This ontological knowledge base, along with logical rules and queries, coincides with Hofstadter's idea of concept networks and sameness detector [Hofstadter, 1979]. Using ontology, we formulated a back-and-forth interaction between each individual and their de-

Table 2: Examples of SWRL rules.

#1	$(LeftSide1\ Has\ ?sha1) \wedge (LeftSide2\ Has\ ?sha2)$ $\wedge(LeftSide3\ Has\ ?sha3) \wedge (LeftSide4\ Has\ ?sha4)$ $\wedge(LeftSide5\ Has\ ?sha5) \wedge (LeftSide6\ Has\ ?sha6)$ $\wedge(?sha1\ Is\_Same\_As\ Quadrilateral) \wedge (?sha2\ Is\_Same\_As\ Quadrilateral)$ $\wedge(?sha3\ Is\_Same\_As\ Quadrilateral), (?sha4\ Is\_Same\_As\ Quadrilateral)$ $\wedge(?sha5\ Is\_Same\_As\ Quadrilateral) \wedge (?sha6\ Is\_Same\_As\ Quadrilateral)$ $- > (Left\ Consists\_of\_Shape\ Quadrilateral)$
#2	$(Left\ Consists\_of\_Shape\ ?a) \wedge (Right\ Consists\_of\_Shape\ ?ab)$ $\wedge(?a\ Is\_Different\_From\ ?ab) \wedge (?ab\ Is\_Different\_From\ Quadrilateral)$ $- > (Left\ Has\_Infered\_Shape\ ?a) \wedge (Right\ Has\_Infered\_Shape\ ?ab)$
#3	$(Left\ Consists\_of\_Shape\ ?a) \wedge (Right\ Consists\_of\_Shape\ ?ab)$ $\wedge(?a\ Is\_Different\_From\ ?ab) \wedge (?ab\ Is\_Same\_As\ Quadrilateral)$ $- > (Left\ Has\_Infered\_Shape\ ?a) \wedge (Right\ Has\_Infered\_Shape\ ?ab)$
#4	$(Left\ Consists\_of\_Shape\ Empty) \wedge (Left\ Consists\_of\_Shape\ null)$ $\wedge(Right\ Consists\_of\_Size\ null) - > (Left\ Has\_Infered\_Shape\ Empty)$ $\wedge(Right\ Has\_Infered\_Shape\ NotEmpty)$

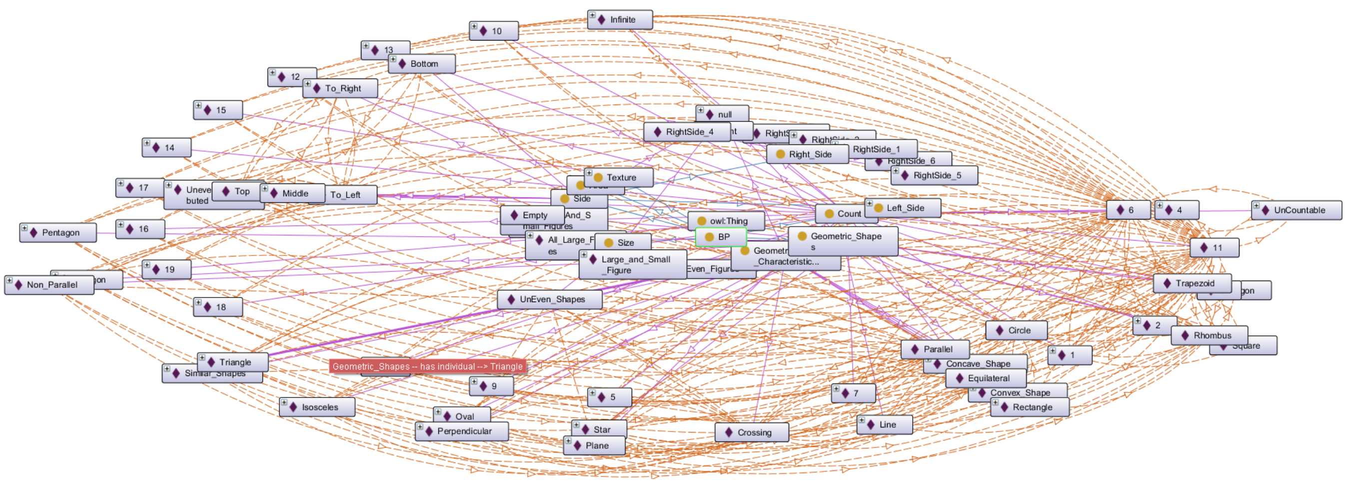


Figure 9: Ontology based concept network

scriptions (where every node is linked to every other node via properties).

It is generally known that the visual cortex in humans helps in the processing of visual information and object recognition. But it is still unclear how the human brain can select a set of minimum possibilities from a wider set of information in the real world. Such conscious recognition of shapes, colors, and so on from an output of visual cortex is a challenging mystery. We implemented a funneling-based approach to narrow down the inferences (i.e., taking the minimum possible decisions from multiple relations).

As shown in Figure 8, the logical rules are formulated in a way to take different levels of inferences to arrive at the most suitable solution. The logical description to Figure 8 is as described in Table 1.

4 Result

In the present study, we formulated a Jena-based ontology was formulated to make machines mimic human cognitive abilities in solving BPs. The static ontological knowledge had 1094 axioms and 38 properties. Twenty-nine logical rules were formulated for logical evaluations. Some of the SWRL rules are provided in Table 2. These SWRL rules are employed to detect the differences in shapes (quadrilaterals and other shapes) that are present at the given two sides of a BP. The SWRL rules in Table 2 are presented in RDF format (Subject, Predicate and Objects [SPO] format). We evaluated this model on a subset of BPs (as shown in Table 3). As mention previously, our main focus was to design a cognitive model for logically inferring the concepts for solving a BP, rather than focusing on computer vision techniques. In our study, a Java-based GUI was used to obtain multiple inputs from a BP solver (human perceived data), as a replacement for the image processing unit. The queried visual information was then converted in RDF form in OWL to depict the short-term memory. The inputs for each box consisted of type of shapes, shape counts, texture (including outlined and filled shapes), size, positional information, and information-related

Table 3: Solution of BPs through ontological implementation.

BP-number	Number of Inferences	T (*sec.*)
BP #1 Left $Has\_Infered\_Shape\ \ Empty$ Right $Has\_Infered\_Shape\ NotEmpty$	First stage Inference = 37 Second stage Inference = 12 Third stage Inference = 2	2.468
BP #2 Left $Has\_Infered\_Size\ Large\_Figure$ Right $Has\_Infered\_Size\ Small$	First stage Inference = 112 Second stage Inference = 12 Third stage Inference = 2	12.985
BP #3 Left $Has\_Infered\_Texture\ \ No\_Filling$ Right $Has\_Infered\_Texture\ Dark\_Filling$	First stage Inference = 102 Second stage Inference = 12 Third stage Inference = 2	12.823
BP #6 Left $Has\_Infered\_Shape\ Triangle$ Right $Has\_Infered\_Shape\ Quadrilateral$	First stage Inference = 144 Second stage Inference = 12 Third stage Inference = 2	20.745

characteristics of the shape.

According to psychological experiments with 31 human subjects by Harry Foundalis [Foundalis, 2006], he reported the BPs were solved by 50% students approximately and he classified as easy, moderate and difficult BPs. In our experiment, 9 easy BPs and 1 moderate BP were applied to the verification test of our proposed system. As shown in Table 3, the system in our ontological approach successfully demonstrated that the 10 BPs were solved and replied the resultant message as the concluding logic to discriminate two groups. As demonstrated in the computer experiment, the perceived information for each BP (from the GUI-based visual instances) underwent funneling and regressive filtering through logical rules to obtain distinction between the left and right sides of a given BP.

5 Discussion

In the same proposed system, it is possible to develop with an automatic generation of the static ontology-based knowledge and SWRL rules, for the generalization of the solver for all 100 BPs. In our hypothesis, we assumed three core architectures as 1) an auto-generative system to represent characteristics in the target picture with primitive forms (autonomous label generator), 2) a semantic network coordinator to find an appropriate representation without redundancy (coordinator/evaluator), and 3) an analogy maker to bind a set of the characteristics and to set a consistent representation in a simple form by ignoring unnecessary parts to conclude (generalizer) as illustrated in Fig.2 and then dealt with the issue whether the idea of the concept network can be implemented and how it effectively solve the BPs. On the other hand, autonomy and generality are placed in issues that we need to tackle. As discussed in Fig.3 (b), a question of what is *'orifice'* which is defined as *'an opening, as of a pipe or tube, or one in the body, such as a nostril.'* from the dictionary, requires the cognitive function to think an abstract way. It is determined by the relational/relative information in cases of BPs, as we demonstrated preliminary, while a further implementation is necessary to involve a probabilistic model [Hernández-Orallo *et al.*, 2016; Saito and Nakano, 1995; Taniguchi, 2017; Salameh *et al.*, 2014].

The concept network was discussed in past studies as models and psychological analyses [Foundalis, 2006; Linhares, 2000]. In comparison with those models and studies, our computational model was build systematically by using the semantic web technologies and reasoning architectures [Maarala *et al.*, 2017; Durbha and King, 2005; Zand *et al.*, 2016; Johnson *et al.*, 2017], which allows us to clarify the future capability to be close in on the human intelligence [Kurzweil, 2014] or an inevitable limitation.

6 Conclusion

In the computer experiment, our system successfully demonstrated that BPs can be solved in the concept network organized with different properties and their combinations, which has a capability to extend more new/abstractive concepts. Using RDF-based rules and queries, pruning of the inferred concepts in the search space using regressive inferences was successfully implemented. In future work, this model can be extended for the complete solver for all 100 BPs and new BPs.

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