Knowledge Based A.I. to the ARC Prize Challenge

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Abstract

The ARC (Abstraction and Reasoning Corpus) Prize Challenge is a benchmark designed to assess the abstraction and reasoning capabilities of A.I. systems. This project will explore how Knowledge-Based A.I. (KBAI) methods can be applied to address its problem solving capabilities of A.I. This document will outline initial attempts on the challenge and the progress made on solving ARC tasks.

The ARC Prize Challenge is designed to push the boundaries of artificial intelligence beyond pattern recognition towards general problem solving. ARC tasks consist of input-output grid transformations that are human-solvable but difficult for machines to automate by using standard machine learning approaches. Each task consists of a unique solution with no clear training data or rules that apply across the problem sets. The key challenge of ARC is to create an AI system capable of abstract reasoning that requires the ability to generalize across different tasks, understand object relationships, and apply transformations that resemble human-like intelligence.

To solve ARC tasks, an A.I. system must be capable of identifying abstract patterns, such as symmetry, mirroring, or repetitive structures. For example, one task may involve rotating a shape, while another may require filling gaps in a pattern. The challenge lies in designing a system flexible enough to infer these rules from very limited training sets.

Knowledge-Based A.I. (KBAI) offers a promising approach to this challenge in many aspects. KBAI methods integrate symbolic reasoning, rule-based systems, and domain-specific knowledge, allowing A.I. to understand concepts beyond simple pixel-level transformations. The question for this project is how KBAI methods can be applied to ARC and what capabilities are needed to develop an A.I. system that can successfully reason through these problems.

Related Work

The ARC Prize Challenge diverges from traditional AI problems such as pattern recognition in large datasets by emphasizing abstract reasoning and generalization. KBAI methods offer a promising approach, especially for tasks like ARC that require an A.I. system to understand and apply higher-level concepts.

One area of inspiration comes from computational models designed to solve Raven's Progressive Matrices (RPM), a family of intelligence tests that also emphasize abstract reasoning. Kunda, McGreggor, and Goel proposed a computational model that used iconic visual representations to simulate modal reasoning, offering an alternative to traditional propositional representations in solving RPM problems. Their model, known as the "affine model," successfully applied transformations like rotation and set operations on visual problem sets, achieving recognizable performance, which can be compared to children aged 9 to 11 years on standard RPM tests. The relevance of Kunda's work to the ARC challenge lies in the approach to reasoning through visual analogy and transformation. The ability to extract and manipulate iconic visual representations may provide a breakthrough to solving ARC problems, which is to perform multiple abstract transformations in a grid-based visual representation. (Kunda, McGreggor, and Goel 2013)

In a more recent study, Chollet (2019) in "On the Measure of Intelligence" argues that current A.I. approaches lack general intelligence, which he defines as the ability to adaptively solve a wide range of problems. Chollet introduces the idea of "meta-learning," where an A.I. system learns how to learn, thus being able to apply knowledge across different fields of problems. This meta-learning concept is highly relevant to ARC, where tasks vary wildly and predefined rules or data-driven methods alone are insufficient for successful results. Chollet suggests that, to succeed in ARC, an A.I. system must develop a form of casual reasoning that can generalize across tasks. (Camposampiero et al. 2023)

These two studies point to the need for a multifaceted approach to solving ARC tasks. Kunda's study highlights the importance of visual and analogical reasoning, and Chollet's work emphasizes the necessity of adaptive, causal reasoning. Together, these insights can inform that the development of more effective A.I. systems for solving the ARC Prize Challenge, moving beyond task-specific solutions to create systems capable of abstract, general reasoning across a variety of domains.

Methodology

The primary structure I used in the initial attempt is a rule-based framework that operates over grid representations. Specifically, the following key elements are incorporated.

- Representation Structures
- Transformational Primitives
- Rule-Based System

Semantic networks and grid-based representations to capture the relationships between different objects and colors within the task grids techniques were utilized. This allowed understanding abstract transformations, such as color changes, trimming, and mirroring. These transformations are organized into a heuristic-driven framework, ensuring that the system prioritizes transformations based on grid properties, such as color variety or grid symmetry. Lastly, the core of the KBAI system, a rule-based system, applies predefined transformations and heuristics, like compressing rows and columns, based on the input grid's structure. These rules allow the system to generalize solutions across different ARC tasks.

Experiments

Initial experiments were conducted through training tasks. In the training task sets, 11 tasks were correctly predicted. In contrast, a poorer score was recorded on the evaluation set. Score 2.0/400.0 was recorded in Gradescope. The correctly predicted tasks only included two, as shown below.

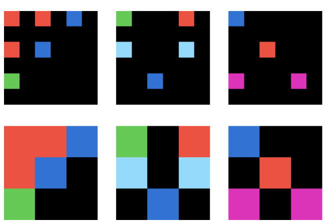

Figure 1: Evaluation 1

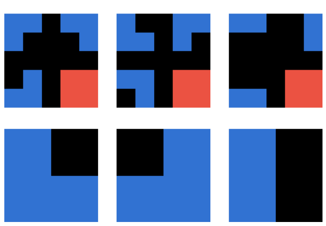

Figure 2: Evaluation 2

Tasks that required the system to infer relationships between objects (such as grouping or complex symmetry) proved difficult. However, the system achieved a moderate score on the training sets, indicating potential for improvement.

Expansion of DSL primitives

The initial improvement phase involved expanding the Domain Specific Language (DSL) primitives to cover a broader set of transformations, reaching 16 custom DSL functions. This set included basic transformations from experiments (e.g., rotation, mirroring) and more task-specific functions (e.g., invert_colors, tile_4x). Later, primitives focusing on object complexity (least_complex_object, delete_least_complex_object, and most_complex_object) were added. These additions allowed the program to handle a wider variety of tasks that required complex object recognition and manipulation.

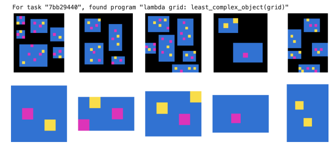

Figure 3: Least Complex Object

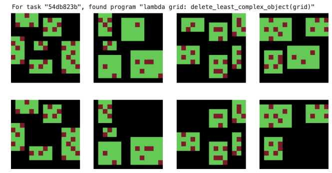

Figure 4: Delete Least Complex Object

Heuristics

As the DSL primitive count grew, so did the potential combinations, with 786,269 program combinations at one point. Testing showed that the program could score 6 points but faced runtime issues in Gradescope, exceeding 30 minutes in Jupyter Notebook. To address this, heuristics were implemented to reduce redundant transformations during program string generation, such as rotating 90 degrees and rotating 270 degrees together. This adjustment effectively reduced the number of programs to 486,259 and runtime to approximately 11 minutes without affecting the program's ability to generate valid transformations. As a result, without raising timeout errors, the score was recorded 10.0/400.0.

Advanced DSL methods

To handle noisy pattern tasks, a correct_noise function was implemented. This function applied impainting techniques to recognize and eliminate noise by matching patterns and colors dynamically. First, the method finds the center of the pattern by comparing the symmetry of the pattern. Based on this center discovered, it searches for equivalent pixel locations to compare and determine noise color. Once the noise color is earned, apply proper color from other pixels to the noise pixel. Due to its costly computation to compare every pixel in the grid multiple times, dynamic heuristics were incorporated. Based on input grid patterns and object characteristics, it filters out unnecessary computations. Thus, further cutting down the runtime to under 10 minutes while scoring 21 points turned out successfully.

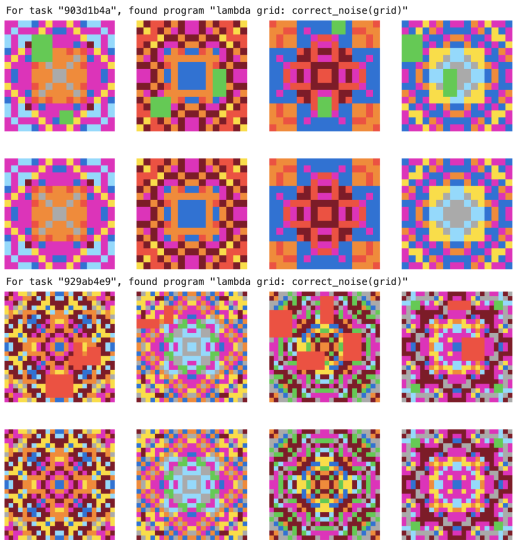

Figure 5: Correct Noise

Dynamic Color Transformation Logic

To address output grids with matching shapes but with color discrepancies, dynamic color transformation logic was introduced. This logic dynamically learned color mapping from training data, allowing transformations where colors did not initially align. The dynamic color transformation boosted accuracy by 50 percent, especially on tasks where minor color mismatches previously caused failures. This, combined with new frame-related DSL primitives, raised the Gradescope score to 30 points.

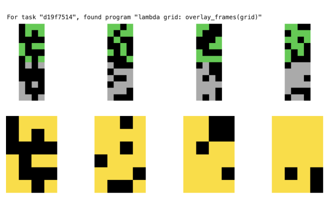

Figure 6: Overlay Frames

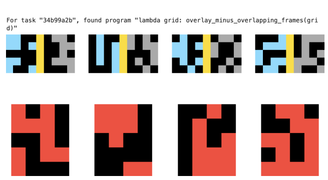

Figure 7: Overlay Minus Overlapping Frames

Results

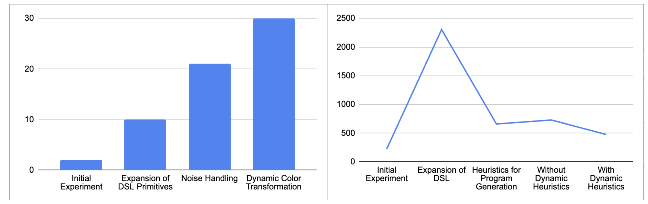

Figure 8: Performance Metrics

- After expanding DSL primitives: Scored 6.0 points, runtime of 2306 seconds.
- After adding object-based primitives and basic heuristics: Scored 10.0 points, runtime of 660 seconds.
- After adding noise handling with correct_noise: Scored 21.0 points, runtime increased to 730 seconds.
- After implementing dynamic heuristics and dynamic color transformation: Scored 30.0 points, runtime reduced to 477 seconds.

Analysis

The expanded DSL primitives set expanded the diversity range of ARC tasks that could be handled. Implementing heuristics was essential for managing computational demands, allowing the program to remain within Gradescope's time limits. The introduction of noise correction and color transformation significantly improved the program's ability to handle variations in grid data, underscoring the importance of dynamic, data-driven adjustments in Knowledge-Based AI.

Discussion

This project investigated the application of a Knowledge-Based AI (KBAI) approach to solve ARC challenges, focusing on utilizing domain-specific knowledge representations and task-specific transformations. In contrast to traditional machine learning, which often relies heavily on large data for training, this approach utilizes specific reasoning techniques, such as object decomposition and symbolic manipulation. By working with a small and interpretable set of primitives, this project highlights the importance of explicit representation and logic within KBAI.

The project findings suggest that task decomposition and symbolic manipulation offer valuable insights into the field of Knowledge-Based AI, particularly in the context of visually grounded reasoning. This approach aligns with the goals of KBAI by leveraging explicit rules, mirroring the reasoning techniques of classic AI systems, and diverging from neural-network-based methods. The results, while limited in scope, indicate that targeted heuristic transformations can effectively address ARC tasks. This project provides an empirical contribution to KBAI by demonstrating how certain forms of knowledge representation can be practically applied to solve visually complex problems.

The approach supports the concepts explored in Camposampiero et al. (2023), where large language models (LLMs) are applied to transform ARC tasks into natural language descriptions for reasoning. While their method broadens the scope to include language-based AI, this project took a contrasting approach by focusing exclusively on visual reasoning primitives. Additionally, Kunda et al. (2013) introduce a computational model using iconic visual representations to solve intelligence tasks. This project adopted their reliance on perceptual and spatial reasoning but used a Knowledge-Based framework rather than a strictly perceptual one, making this work a bridge between KBAI and iconic representation strategies.

The project has demonstrated that structured, knowledge-based methods can effectively address ARC challenges, underscoring the value of symbolic representations in AI reasoning tasks. The main claim derived from this work is that rule-based knowledge processing can provide a pathway to solving visually complex tasks without the need for data-driven training. This fits ARC's goal to evaluate AI's capacity for generalization, supporting the hypothesis that KBAI approaches can yield robust solutions under limited data conditions.

Conclusion

In summary, this project contributes to Knowledge-Based AI research by showcasing a symbolic and heuristic-driven method for solving ARC tasks. By focusing on domain-specific transformations and utilizing a handful set of primitives, the project demonstrated the potential of KBAI methods in achieving task-specific problem-solving in AI. The findings suggest that KBAI principles, such as decomposition and explicit rule application, can bridge certain gaps left by data-intensive learning approaches. This provides valuable insights for KBAI research in fields like computer vision and visual reasoning.

Future Work

The project opens several directions for future research. First, expanding the library of primitives to include more complex symbolic operations could improve versatility in solving diverse ARC tasks. Furthermore, integrating aspects of perceptual reasoning, as seen in Kunda et al. (2013), could bridge perceptual and symbolic reasoning, potentially enhancing the model's robustness. Finally, exploring hybrid approaches, combining KBAI methods with minimal data-driven techniques, might yield a more adaptable and resilient solution framework, enabling AI systems to tackle a broader range of reasoning tasks.

References

Journal Article Kunda, M., McGreggor, K., and Goel, A. 2013. A Computational Model for Solving Problems from the Raven's Progressive Matrices Intelligence Test Using Iconic Visual Representations. Cognitive Systems Research 22–23: 47–66. doi:10.1016/j.cogsys.2012.08.001.

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