Final RPM Project Report

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1 AGENT DESCRIPTION?

My agent takes a hybrid approach between two approaches:

1. Dark Pixel Ratio / Intersection Pixel Ratio (DPR/IPR).
2. Breakdown of Images into its shapes and checking for various transformation cases using OpenCV.

For a given problem, the agent first implements (2) and checks for relevant heuristics. If the cases fail and no solution is found, it then falls to trying various algorithms in (1) to propose a solution.

1.1 DPR/IPR

DPR/IPR implement a number of algorithms to check for patterns.

- Logical AND, OR and XOR (3x3 problems only): the NumPy logical function is applied between [A,B] (example, [A and B], [A or B], [A xor B]) and checked against C using IPR with a threshold. IPR is defined to be intersection of two binary images divided by their union. If that passes, then logical of [D,E] is checked against F. If this passes as well, then the agent has successfully detected this pattern, and now forms a solution by taking the logical of [G,H] and comparing it with each of the answer options. The highest-scoring answer option is returned.
- Pixel addition and subtraction (3x3 problems only): This checks for the pattern where pixels are being added or subtracted in subsequent images. Dark pixels (pixels <= 254), are calculated for each image, calculating the Dark Pixel Count (DPC). DPC of A is added to DPC of B, and compared with DPC of C with a threshold. If that passes, then same is done for D, E, and F. If this passes, then DPC of G and H is added and compared to each answer option's DPC, returning the closest match. Same is done with the subtraction method.
- Diagonal IPR Comparison (3x3 problems only): This checks for the pattern found in Problem Set D where the connected images are not in

the same row/column using IPR as the comparison heuristic. If the IPR of [A,E] are above a threshold (then they match!), and at the same time, A should not be similar to B, C and D, so those IPR combinations should be less than a threshold. If this check passes, then the agent assumes the answer's IPR is closest to E. If this fails, then the method is repeated by checking for the case where, instead of A and E, images B and D are similar.
    - This method includes a sub tactic of excluding answer options that already exist in images A-H, aka, checking for duplicates, to increase accuracy.
- The last algorithm acts as a failsafe when none of the above pass. This gets the DPC in images A, C, and answer options 1-8. It then gets the scale factor of DPC from image A to image C and applies it to G's non-white pixel count to get a DPC for '#' (aka the answer). It then compares the new answer to that of each of the answer options and returns the closest match as the answer.

1.2 Breakdown of Images

This algorithm breaks an image down into the shapes it consists of. Here is the step-by-step process:

- Classify each image into separate shapes using cv.connectedComponentsWithStats(), which retrieves the bounded rectangle and centroid, among other features.
- Extract information about each shape such as its number of vertices (cv.findContours), number of approximate vertices (cv.approxPolyDP; in case of shapes with circular curvature having hundreds of vertices), whether the shape is solid or hollow, perimeter or arc length (cv.arcLength), enclosed area (cv.contourArea), non-white pixel count, aspect ratio of its bounded rectangle, and centroid.
- Extract relationships between two given shapes; rotation, translation, scale factor, whether they have the same solidity/hollowness, whether they have the same center, and whether they are the same shape.
- Transform the shape with the relationship and recreate it using cv2.polylines().

- Compare the transformation to answer options comparison of extracted information variables.
    - The method for comparing to images is to check the features of each image (number of shapes, vertices, etc.).

Some additional patterns this method checks for:

- The pattern in problem set D where similar images are found in a different row/column. The agent goes through each of the 8 (A-H) images and compares each of them to check whether they are the same image. If the agent finds two images repeating three times (not in the same row or column) and one image repeating twice, then it goes into this case. It then reports the answer to be the image that repeated only twice.
- Vertex addition and subtraction patterns; these addresses problems where the number of vertices in a shape increases linearly between images in the same row. The algorithm detects the number of vertices each shape increases by, adds it the number of vertices in image H, and looks for that number of vertices in the answers. If it finds it, then returns that answer.
    - This also excludes duplicate answer options found in images A-H.

Finally, the agent has hardcoded data of all the relevant DPC/IPR values calculated from the Basic and Challenge Problems provided to us and applies that to get a guaranteed correct answer for those problems on Gradescope.

2 AGENT PERFORMANCE

My agent scores 77/96 on Gradescope; it passes all Basic and Challenge problems, 29 Test problems, and 25 Raven's problems. More specifically, it passes 6/12 Test B, 6/12 Test C, 7/12 Test D, and 9/12 Test E problems; 8/12 Raven's B, 7/12 Raven's C, 4/12 Raven's D, and 6/12 Raven's E problems. Without the hard coding of the given problems, it scores 59/96 on Gradescope.

3 AGENT SUCCESSES

Figure 1 shows three problems my agent correctly answers.

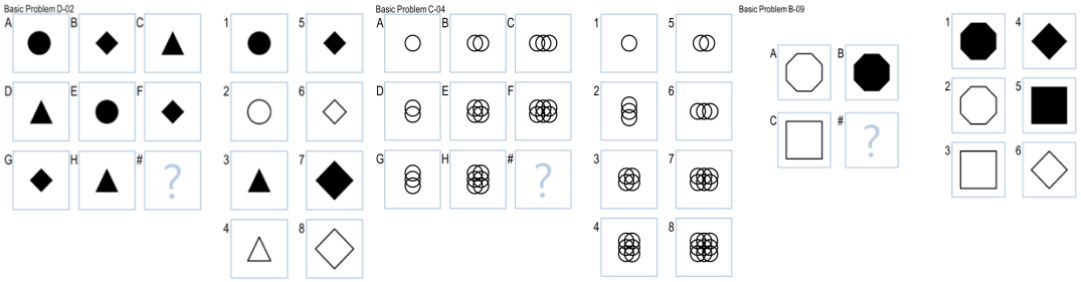

Figure 1: Agent's successes

- Basic Problem D-02 uses the shape detection method to look for a pattern where similar images are found in a different row/column. It detects that the triangle and diamond shapes occur thrice, but the circle occurs only twice, so it searches for a circle in answer options 1-8 and correctly reports 1 as the answer.
- Basic Problem C-04 uses the DPR failsafe method. It calculates the DPR between images C and A, applies that to the DPC of image G to generate a DPC for image #, then looks for the answer with a DPC closest to that value, correctly reporting 8 as the answer.
- Basic Problem B-09 uses the shape detection algorithm to get relationships between images A and B, and A and C. The latter revels no relationships to the agent (even though the polygon gets replaced by the square), but the agent is able to detect that the shape gets solid from A to B. So it generates a solid square as an answer for #, and correctly reports 5 as an answer by looking for it in the answer options using shape feature comparison.

4 AGENT STRUGGLES

Figure 2 shows two kinds of problems my agent struggles with and answers incorrectly.

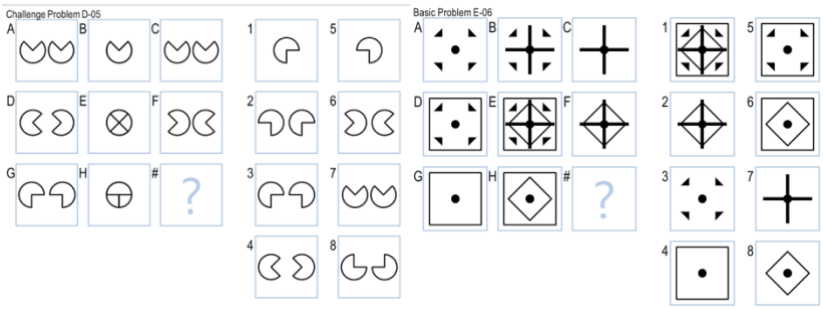

Figure 2: *Agent's struggles*

- Challenge Problem D-05: (note that this is an evaluation of my agent based on the efficacy of its methods without the hardcoded values designed to increase score) This problem exhibits two shapes moving in opposite directions, intersecting in the middle column, and being on opposite sides in the third column. I did not program my agent to detect this pattern (without overfitting to this particular genre of patterns), although it is possible to do so. The correct answer is 2.
- Problem E-06: This is an XOR case, which my agent has been programmed to detect in the DPR/IPR method. The agent fails to detect this pattern and provide a correct answer because of an anomaly not considered in the agent's programming: the middle solid circle is never removed from the third column even though it is present in the first two columns. This makes the agent not pass the threshold value and think the pattern of XOR is not there. The correct answer is 8.

Overall, my agent generally solves simple problems with simple relationship mapping or DPR/IPR patterns, but is not able to solve more complicated problems with nuances such as those described above.

5 AGENT DEVELOPMENT – DESIGN APPROACH

The agent uses a waterfall approach where it evaluates a given problem through multiple pattern-recognition algorithms one by one. If it passes an algorithm earlier on the list, the answer is returned, and the later algorithms are not considered. In this case, the shape recognition is performed first. If that fails, then DPR/IPR algorithms are used.

In Milestone 2, the agent only had image transformation techniques such as rotation and translation coded in. It did not have any shape detection features or

DPR/IPR. Milestone 3 saw an evolution of a simple DPR (scaling factor only) approach, which got a score of 100 on Gradescope. This approach also scored full points for Milestone 4, but by that time I had realized that the DPR/IPR approach might not be enough for a high score on the final project, so I then programmed shape detection into the agent. For the final project, the agent was programmed with a plethora of new algorithms (general IPR, vertex addition/subtraction, and/or cases with IPR, etc.) that I saw as low hanging fruit to increase its score; much of the credit is due to the discussions in the forums that helped me think of new approaches.

The overall approach to designing my agent was an iterative one. Given constraints of patterns and images, the agent was initially programmed with a simple image transformation approach, which was then abandoned for more sophisticated ones when the level of difficulty increased in subsequent milestones, i.e. a change of constraints was observed. Hence, the problem and solution co-evolved, as we were taught in the Design Lesson.

6 SIMILARITY WITH A HUMAN

The agent has some similarities but perhaps more differences; here is how it is quite different from how a human would approach the test:

1. There is no meta-cognition programmed within the agent. The agent can neither learn from its mistakes, nor can it recognize that it was wrong, unlike a human who would reflect on their reasoning to fill in gaps in reasoning, knowledge, and or learning to improve its reasoning.
2. Humans, and often I, can often subconsciously solve simple RPM problems without explanation-based reasoning, i.e., without having to mentally extract and explain features from images in a problem, by just detecting patterns by what they see. The agent does not have this capability.
3. The agent has an extent to which it can understand patterns and relationships amongst different images, whereas humans (at least our age group and up) might have a much deeper understanding and knowledge of visual patterns and cues from all previous experiences gathered so far.

4. Humans, if needed, can easily resort to analogical and explanation-based reasoning, whereas this agent cannot.
5. Finally, of course, the agent is much faster at solving these problems than a human is.

In terms of similarities, the agent uses visuospatial reasoning (to an extent, similar to humans) to process and establish relationships between images and shapes. A sub-similarity of this between this agent and myself (and humans in general) would include the extraction of various meaningful features to solve a problem (vertex addition and subtraction, transformation mapping, etc.).

In conclusion, the agent seems to be more different to humans than similar and is still not yet in a form I would deem as 'robust' enough. However, I am happy that it performed at an 80% accuracy on Gradescope; granted that it did learn all the provided cases perfectly. This is another similarity since this is what a human might do if they were to prepare for a test; we would memorize or perhaps truly understand the problems we have already seen in our 'preparation' and learn the answer (by correction of mistakes and/or by recording cases).