Mini Project 4 – Monster Identification

Michael Lukacsko
mlukacsko3e@gatech.edu

1 AGENT IMPLEMENTATION

The agent works by employing a feature-based matching approach to classify a new monster as belonging to a specific species or not. It starts by analyzing the labeled samples, which are provided as a list of monsters where each is either marked as an instance of the species (positive) or not (negative). For each monster, the agent extracts its attributes and organizes these attributes into two sets: one for the values observed in the positive samples and another for the values observed in the negative samples.

Once the agent has collected this information, it processes the unlabeled monster by comparing each of its attributes to the values seen in the positive and negative examples. For each attribute, if the value matches one observed in the positive samples, it increments a count of positive matches. Similarly, if the value matches one seen in the negative examples, it increments a count of negative matches. After examining all the attributes, the agent compares the number of positive matches to the number of negative matches. If the new monster has more attributes that align with positive examples, the agent classifies it as belonging to the species by returning True. Otherwise, it classifies the monster as not belonging to the species and returns False.

This approach can be likened to a simplified form of nearest-neighbor classification, where the agent evaluates how closely the new instance resembles the positive and negative examples based on its features. As described in the assignment description, the agent assumes that each feature is independent and equally important, which allows it to make a straightforward classification decision based on matching attributes.

2 AGENT PERFORMANCE

Based on the Gradescope results, the agent performs well, correctly classifying 17 out of 20 monsters, giving it an overall success rate of 85%. It successfully identifies most monsters, including those tested locally and most of the others provided by the autograder. However, the agent struggles with three specific cases—monster_3, monster_4, and monster_9—resulting in 3 incorrect predictions. Notably, monster_3 and monster_4 were part of the test cases provided, meaning the agent was expected to handle them, but it failed to do so.

In the case of monster_3, the agent likely fails due to feature overlaps between positive and negative examples. For instance, the attributes 'large' size, 'fur' covering, and 'foot' type are present in both positive and negative samples, causing confusion in the agent ability to classify it. Similarly, for monster_4, features like 'black' color and 'paw' foot-type appear in both positive and negative examples, while the 'scales' covering is associated with negative examples, leading to the agent's incorrect decision. These cases suggest that the agent struggles when there is significant overlap in the features of positive and negative examples, making it difficult to differentiate them.

Overall, the agent handles most straightforward cases effectively, but it could benefit from improvements such as feature weighting or handling ambiguous attributes better to perform more accurately in these tougher, edge-case scenarios.

3 AGENT EFFICIENCY

Figure 1 below is a visual representation of the agent demonstrating strong efficiency across all 14 test cases (4 provided test cases plus 10 additional), maintaining a consistent performance in terms of time taken to classify each monster. Among all the test cases, the first two take the longest to solve, with times of approximately 0.000018 seconds and 0.000017 seconds, respectively. These two likely take longer due to their complexity and the agent's initial processing. After these first cases, the remaining 12 test cases average around 0.000015 seconds, reflecting the agent's ability to quickly process each classification task. The agent operates in a linear fashion, where the time taken increases in proportion to the complexity of the comparisons, but it remains highly efficient.

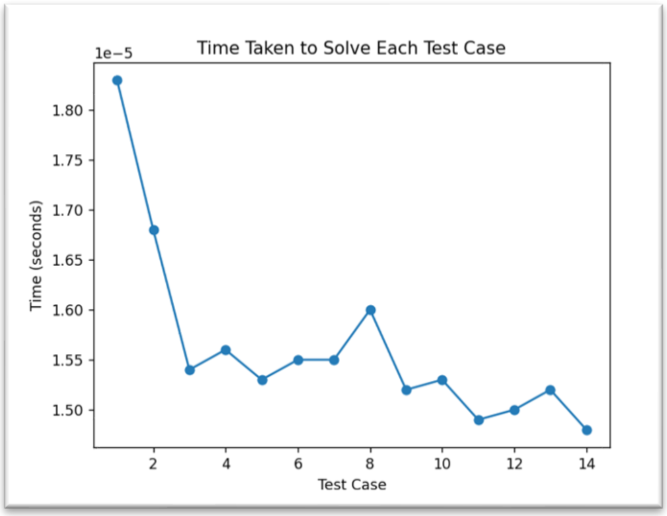

Figure 1—Monster Identification – Time taken for test cases

4 YOU CLEVER AGENT!

The agent does not employ any particularly clever or advanced optimization techniques to arrive at an answer more efficiently. Its approach is relatively straightforward, relying on a comparison of the attributes of the new monster against the attributes of the labeled examples. While this method is simple, it is effective because it avoids unnecessary complexity, allowing the agent to perform consistently well even as the dataset grows. The agent operates linearly, meaning it checks each attribute independently, without using more complex algorithms like decision trees, machine learning models, or probabilistic methods. This simplicity is a strength in this context, as it minimizes computational overhead while still providing accurate classifications.

5 AGENT VS. HUMAN

The agent's approach to classifying monsters is heavily systematic and based solely on feature comparison, which is somewhat similar to how a human might approach these problems. Like the agent, a person would likely identify patterns in the known monsters and use those patterns to classify new monsters by comparing specific attributes like size, color, or the number of limbs. However, humans tend to apply more flexible reasoning, often weighing certain features more heavily based on intuition or experience, while the agent treats all attributes as equally important. Additionally, people can make inferences based on context and may recognize relationships between attributes that the agent would not—such as identifying that a monster with wings is more likely to lay eggs, even if that exact combination wasn't seen before. While the agent performs a straightforward, consistent analysis, a human might rely on generalization, exceptions, or even biases when classifying new examples.