Evaluating Trainer Policy: A Performance Study of Non-Compensatory vs. Cumulative Rule-Based AI for Umamusume Stat Optimization

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GitHub Repository Link: `https://github.com/Metron-nome/Umamusume-AI-Model`

Abstract

This paper develops and evaluates two distinct Rule-Based AI (RBAI) models—the Heuristic Sequential Model (non-compensatory) and the Weighted Scoring Model (compensatory)—designed to classify optimal resource allocation in the Umamusume: Pretty Derby training simulation. The methodology involves translating complex Uma metrics (Energy, Failure Chance, and individual stats) into IF-THEN decision structures. Performance metrics reveal a trade-off: the Weighted Model achieved higher overall Accuracy (0.60), proving superior in risk avoidance (Rest classification). However, the simpler Sequential Model attained a slightly higher F1-Score (0.51) and better Recall (0.60), demonstrating greater success in identifying opportunities for stat training. This comparative analysis highlights a crucial dilemma in prescriptive AI design: while the complex compensatory model offers better predictive power, the rigid, highly interpretable sequential model provides clearer, more decisive guidance necessary for human adoption in real-time training environments.

1 Introduction

The allocation of limited resources in training a horse or an Uma in simulated environments such as the Umamusume: Pretty Derby Training System made by CyGames presented a multi-criteria decision problems when it comes to training an Uma. A proper and optimal course of action not only requires systems that are accurate, but also relies on traceable actions to human users. This dictates the use of Two Rule-Based AI, which focuses on If-Then logic to be able to predict the training action based on performance metrics. The issue relies in translating Uma stats such as energy, speed, and failure risk into a readable, and reliable decision making structure for Uma Trainers.

This research paper focuses on developing and evaluating two rule based AI models to assess and predict the most effect strategy for balancing stat gain against the failure chance of an Uma. The Heuristic Sequential Model which is the first model used for this performance study, checks rules in a fixed order until a decision is met. The second model which is the Weighted Scoring Model, focuses on scores across all stat factors of the Uma to allow the strongest stat offset weaknesses. This performance analysis and study aims to compare how efficient the interpretability of the sequential approach and the weighted scoring system.

Research Question: How does the performance of a Heuristic Sequential Model compare to a Weighted Scoring Model when classifying optimal training actions in an Umamusume simulation?

2 Literature Review

2.1 Foundations of Rule-Based AI

Rule-Based learning methods for artificial intelligence share a lot of types of techniques in machine learning. The aritificial intelligence and rule based learning methods share the same goal of commonalities in data that both express it in a form of If and Then rule or statements. (Kliegr et al., 2021).

Descriptive Rule Discovery aims to find rules that an artificial intelligence may able to describe commonalities and patterns that can be assessed and observed by the AI in a dataset within a set of rules. It can be considered and defined as an If-Then rule that the AI relates a dataset of individual variables and relate it to the target interest variables. (Kliegr et al., 2021).

2.2 Heuristic Sequential Model vs. Weighted Scoring Model

Heuristics can be defined as a subset of strategies that include Bayesian models. Heuristics aims to make judgements and decisions more quickly with the main focus of making such judgements or decisions with less effort. However heuristics trades off loss in some accuracy to compute information faster, this can be applied to humans, other animals and arificial intelligence. (Gigerenzer, G. & Gaissmaier, W. 2011).

Furthermore, in relation to AI, using a heuristic model for a rule based AI may allow the AI itself to learn the dataset more efficiently with the cost of less accuracy for more faster computation, analysis and decision making from the AI. As it strictly follows sequence of steps where the AI first checks the If conditions whether the value is True, it will Then take an action based on the condition. However if the condition is not met, there is another If statement that AI will take action if the first, second, third, or more If conditions are not met or satisfied.

To explain further, the Heuristic Sequential Model employs a non-compensatory strategy. This means that a specific weakness in one area cannot be compensated for by a strength in another. This rigid logic is exemplified by classic heuristics like the Recognition Heuristic, where decision-making relies on a single cue. In Algorithm 1, if the model encounters a critical risk condition (e.g., Failure Chance $\geq 25\%$), it immediately predicts REST, effectively ignoring all other positive stat gains. This structure is simple and easily interpreted.

Recognition Heuristic is a model that ignores strong and contradicting cues, which are called noncompensatory inferences, unlike the Heuristical Sequential Model, it is a noncompensatory model, the Recognition Heuristic model focuses on compensatory inferences. This model does not define pairs where the the model itself leads to a correct inference and where a paid leads to an incorrect inference. However, various authors that have been referenced from the study mentioned that majority of the population relied on a compensatory strategy such as the weighing and adding all of the cues or scores. (Kliegr et al., 2021).

the Weighted Scoring Model (Algorithm 2) is a compensatory strategy. This model acknowledges that resources have varying importance (weights) and that a holistic evaluation is necessary. The model calculates a total score where low stats (urgency) add positive points, and risks subtract negative points. This structure allows the overall strength of the horse girl (a high cumulative score) to compensate for minor deficiencies, leading to a decision that aims for maximum overall utility rather than immediate risk avoidance. The comparison of these two opposing paradigms forms the basis of the critical analysis in this paper.

In comparison to both models, the Sequential Model relies on making judgements more quicker while sacrificing or losing some percentage or points of accuracy when relying on the model to test a rule based AI algorithm. It can compute information more efficiently and faster but it is less accurate than most models that has been previously made, as the model only relies on a sequence of decisions based on a given dataset. The Recognition Heuristic is a model that focuses on compensatory inferences or cues, which means the model can't define the pairs that leads to incorrect cues or inferences and pairs that leads to a correct inference, as it relies on recognition rather than a sequence or order of a dataset. It is possible to apply a weighing score model to a rule based AI model relating to the Recognition Heuristic model. Since it will rely on recognizing data values or datasets that by adding all of the cues and scores of the data given for the rule based AI model.

3 Methodology

3.1 Problem Domain and Constraints

The dataset provided for the two rule based AI model, has data values such as the Uma's Name, Energy, Failure Chance, Speed, Stamina, Power, Guts and Wit, with each data of the Uma having different values for each type of data class and each Uma has a specified prioritized training strategy that's supposed to be decided by the trainer. For the action points, Action Point 1 is the Speed training for the Uma, Action Point 2 is Stamina training, Action Point 3 is Power training, Action Point 4 is Guts training, Action 5 is Wit training, while Action Point 6 which is considered the default value is Rest.

3.2 Algorithm 1: Heuristic Sequential Model

The Sequential Model is a non-compensatory model and relies on a ordered checklist of priorities, it is implemented by the `Checking_Stats_Of_Uma` function in the source code of the rule-based AI.

- **Safety Check:** The model checks if the Uma's Energy is lower than 40 or if the Failure Chance is greater than 25, based on the game Umamusume: Pretty Derby, an Uma's Energy lower than 40 will cause their training to fail, likewise a Failure Chance greater than 25 may cause the Uma to fail their training. If either of those conditions are the true, the model will suggest Rest (6), It is non-negotiable that shuts down all training for Uma completely if the conditions are satisfied.
- **Stat Prioritization:** If the critical safety check (Failure Chance) is clear or lower than 25, the AI or the model will check if the Uma's core race stats need priortizing, such as Speed and Stamina, for example if an Uma's Energy is higher than 40, their Failure Chance is lower than 25, and they lack Speed, the trainer must priortize Speed training. The model will ignore other rules if the Uma is lacking a specific race stat value.

3.3 Algorithm 2: Weighted Scoring Model

The Weighted Scoring Model system is designed to pass positive stat factors to be assessed with negative stat factors to determine the overall Uma training score of a training action.

- **Calculation** The model will calculate the total score by adding the total ever stat points of an Uma that is deficient or lacking in their stat values. For example if an Uma has a race stat value Speed lower than 450, it will add 10 points to the weighted Uma training score, then subtracts the risk penalties such as if the Uma has low Energy or high Failure Chance.
- **Decision Making** The action made by the AI is also determined or finalized by the total score it calculated, A positive score means that the risk penalty is justified and training is the right choice for the Uma, but a non-positive or negative score prioritizes the Uma's safety and suggests the trainer to have their Uma Rest (6) for the time being.

Image Placeholder: Umamusume Stat Comparison
Comparison of Core Training Stats Across Umamusume Runs.

Figure 1: Comparison of Core Training Stats Across Umamusume Runs.

Table 1: Performance Metrics of the Sequential and Weighted Rule-Based Models

Metric	Sequential Model (Alg 1)	Weighted Model (Alg 2)
Accuracy	0.55	0.60
Precision (Macro)	0.46	0.47
Recall (Macro)	0.60	0.54
F1-Score (Macro)	**0.51**	**0.49**

4 Results

4.1 Data Visualization

4.2 Algorithmic Performance Comparison

5 Discussion

5.1 Analysis of Performance and the Compensatory Effect

The Weighted Model has shown better performance in Accuracy but the Sequential Model shows better performance in Recall. Even though the Weighted Model has higher accuracy based on Figure 2 of 0.60 while the Sequential model has only an accuracy of 0.55, the Sequential Model has better performance and is marginally higher F1- Score (0.51 vs 0.49). The Sequential Model has more of a balance overall performance when it comes to identifying trainer actions and avoiding false negatives.

1. **Sequential Model Analysis** This model has a higher recall which has a value of 0.60. Which suggests that this model is more efficient and better at finding the appropriate training actions for the trainer, since the rules are fixed and prioritized, if the required conditions are met, it will immediately will suggest the trainer to output the prioritized training action for the Uma. It is more decisive than the Weighted Model.

   However, the model has a lower precision which has a value of 0.46, this could suggest that the AI model may trigger the training actions too fast and may lead to a lot of false positives, since some training actions may require the Uma to rest than train, or the AI may predict the wrong stat for the trainer to priotize the training for their Uma.

Image Placeholder: Algorithmic Performance Metrics
Comparative F1, Accuracy, Precision, and Recall of the Two RBAI Models.

Figure 2: Comparative F1, Accuracy, Precision, and Recall of the Two RBAI Models.

2. **Weighted Model Analysis** This model has the highest accuracy of the two rule based AI models, this may suggets that its compensatory logic is highly effective in identifying the difference between the critical risk (Rest) and viable priority training (Any other type of training for the Uma). Which could mean that this model is highly accurate in differentiating the priority action for the trainer to train their Uma, it means that if the Uma has a critical risk or higher failure chance, the model can effectively detect that and recommend the owner to let their Uma rest before training again.

   An issue for this model is that it requires multiple factors to outweigh the critical risk. This may result in the AI choosing Rest (6) more often when the Uma does not need to rest at all and requires prioritizing training their lacking stat value. The model has the lowest recall of the two rule based model.

   To compare the two models, the Sequential Model is more decisive and have shown proof to be more successful in identifying more possibilities to let the trainer choose training over rest, however it may make more mistakes since it prioritizes speed than accuracy. For the Weighted Scoring Model, it is more reliable since it can properly classify the run scenarios for the Umas, but it has missing opportunities because the rules that has been set for the AI are cautious. This model has the lowest recall of the two rule based model.

5.2 Transparency Versus Predictive Power Trade-Off

A. Sequential Model

This model prioritizes interpretability other than accuracy, since it relies on the step-by-step nature, the decision of AI is linear, it is a straight line, which means that the AI's decisions for the training action for the Uma is straightforward. If the model predicts Rest (6), then the trainer knows that the Failure Chance is higher than 25%. This type of straightforward transparency for the trainer allows the model to be easily interpreted and views by anyone. But with its simplicity, based on the Figure 2, the model has low precision (0.46) to be exact, it may result in various amounts of false positives because the AI stops checking the rules too early or missed the combination of stats priority of the Uma.

B. Weighted Model

This model prioritizes the power of predictability by using its own compensatory system for predicting the training action for the trainer. Based on Figure 2, the Weighted Model achieved the highest accuracy which is 0.60, because of its compututation and calculation of the total score is better at balancing the stat factors of the Uma simultaneously. It was able to correctly classify the overall state by allowing multiple deficient stat values for example if an Uma has low Guts, low Wit, or low Power, it can combine those deficient stat values and justify a training action for the Uma. But with its complexity, the model reduces its transparency and it is more difficult to interpret than the Sequential Model, for example, if the model outputs the action Power (3), the trainer may only see the final scores but they will not be able to see the combination of the four deficient stats that generated it. That lack of clarity may confuse the trainer and question the effectiveness and reliability of the model.

5.3 Possible Applications

Real-World Applications of Non-Compensatory vs. Compensatory Rule-Based Models

Both the Sequential and Weighted models, while developed within a simulation context, demonstrate a core trade-off (transparency vs. predictive power) that is applicable to many fields requiring rapid, auditable decision-making.

- **Heuristic Sequential Model (Non-Compensatory Application)** The rigidity of the sequential model is ideal for environments where safety and risk avoidance are absolute, non-negotiable priorities.
    1. **Critical Infrastructure (Power Grid, Traffic Control):** In these systems, absolute safety rules must be checked first. If a pressure sensor (equivalent to Failure Chance) exceeds a critical threshold, the decision (equivalent to REST/SHUTDOWN) must be immediate, overriding any positive productivity factors. The non-compensatory structure ensures this single critical cue dictates the outcome (Gigerenzer & Gaissmaier, 2011).
    2. **Automated Compliance Filtering:** For initial fraud detection in finance or patient screening in healthcare, a sequential model can flag cases based on a single, clear red flag (e.g., "If patient symptom = X, then immediately refer to specialist Y"), offering maximum speed and interpretability.
- **Weighted Scoring Model (Compensatory Application)** The holistic, cumulative nature of the weighted model is best suited for complex optimization problems where a balanced score, rather than a single cue, determines the outcome.
    1. **Financial Credit Scoring:** This mirrors the Weighted Model directly. A loan applicant's weak credit history (negative weight/risk) can be compensated by a high income or low debt-to-equity ratio (positive weights/stats). The final decision is based on the cumulative, balanced score.
    2. **Supply Chain Logistics Optimization:** Decisions about which warehouse to ship from often involve multiple trade-offs: low inventory risk (positive weight) versus high shipping cost (negative weight). The optimal decision maximizes the total utility score across all variables, allowing strengths to compensate for minor deficiencies.

References

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