

**Foundations of Artificial Intelligence**

***Al Ludo Game***

***Team number: Group 11***

***Zaid J Adam***

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**Document Control**

**Work carried out by:**

| **Full Name** | **Email Address** | **Exhaustive list of Tasks** |
| --- | --- | --- |
| Zaid J Adam | zja5160@psu.edu | Project – AI Ludo Game |

**Revision Sheet**

| **Date** | **Revision Description** |
| --- | --- |
| 2/19/2025 | Looking for examples and codes on GitHub - Started writing project proposal |
| 2/24/2025 | Wrote project proposal report |
| 3/8/2025 | Found AI Ludo Game in GitHub |
| 3/22/2025 | Coverted the the Game from py to cells to be able use it in Jupyter Notebook |
| 3/29/2025 | Started analysis game code and create dataset for the game |
| 4/15/2025 | Trained AI and start writing the Report |
| 4/29/2025 | Sumbit Game Coding in ipynb, Report, & Presentation |

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# Introduction

Ludo is a classic board game that has been enjoyed by players of all ages for centuries. Originating from the ancient Indian game "Pachisi," Ludo has evolved into a globally recognized game that involves strategy, luck, and decision-making (Bhattacharya & Sen, 2020). Traditionally played with physical boards and dice, the game has seen significant digital transformation with the advent of technology. Today, artificial intelligence (AI) is increasingly being integrated into board games to enhance the gaming experience, providing both entertainment and competitive challenges for players (Gandhi, Patel, & Sharma, 2021).

In this project, I will develop an AI-powered Ludo game using Python and the Pygame library to implement both visualization and game mechanics. The AI will be designed to make strategic decisions, optimizing gameplay while ensuring a balanced experience that maintains both challenge and fairness for players.

* Development of a fully operational Ludo game featuring an interactive graphical user interface (GUI) utilizing the Pygame library.
* Design and integration of an AI opponent capable of engaging with both human players and other AI agents.
* Implementation of advanced AI strategic frameworks to improve decision-making processes, adaptability, and competitive performance.
* Systematic evaluation of AI performance, focusing on metrics such as decision efficiency, strategic robustness, and adaptability across varied gameplay scenarios.

# Problem Statement

Traditional Ludo games rely heavily on random chance, with limited strategic decision-making for players or AI agents. There is a lack of Ludo games that integrate AI capable of dynamic, strategic play while maintaining fairness and engagement. This project aims to design and develop an AI-powered Ludo game using Python and Pygame, where the AI makes intelligent, adaptive decisions. The goal is to create a more competitive and enjoyable gaming experience for both human players and AI opponents, and to analyze AI performance across varied gameplay scenarios.

Initially, my plan was to have the game generate a dataset in real-time during gameplay and automatically save it as a CSV file in the game folder. However, this approach caused memory issues and game freezing, making it unfeasible. As a solution, I uploaded pre-recorded Ludo gameplay to generate the necessary dataset for the first part of the project focused on gameplay simulation and AI development.

To develop a robust AI system for Ludo, I will:

* Implement a rule-based AI strategy to establish a baseline for decision-making in Ludo.
* Explore advanced AI techniques to enhance decision-making efficiency and adaptability.
* Evaluate AI performance in various game scenarios, ensuring competitive yet fair gameplay for AI opponents.

This project will analyze different AI approaches, comparing their effectiveness in balancing strategic play with the randomness inherent in Ludo. The development of an AI-powered Ludo game presents unique challenges due to the combination of randomness and strategic decision-making. Unlike games such as Chess or Checkers, where AI can evaluate all possible moves using deterministic search algorithms, Ludo relies on dice rolls, making it difficult to predict exact outcomes. Despite this randomness, strategy plays a crucial role, as players must decide which token to move based on board position, opponent threats, and the goal of reaching the finish line (Gupta & Sharma, 2021). Therefore, the AI must balance probabilistic decision-making with strategic play to ensure competitive and fair gameplay.

A common approach to AI in board games is heuristic-based decision-making, where predefined rules guide the AI’s moves. In Ludo, this may involve prioritizing token safety, maximizing forward movement, and blocking opponents when possible. However, rigid rule-based strategies often struggle in dynamic game scenarios. To improve adaptability, reinforcement learning techniques could be explored, allowing the AI to learn from experience and optimize its decisions over time (Patel, Joshi, & Verma, 2020).

Furthermore, Ludo is a multiplayer game, meaning AI must adapt to varying opponent behaviors and shifting strategies. Unlike two-player games, where AI can focus on a single opponent, Ludo requires assessing multiple threats and opportunities simultaneously, adding complexity to AI decision-making (Kumar & Singh, 2019). Efficiently implementing such an AI without excessive computational overhead is a key challenge.

Through this project, I will evaluate different AI techniques, from rule-based heuristics to adaptive learning methods, to determine the most effective approach for creating an intelligent Ludo-playing agent. The goal is to enhance gameplay by providing a competitive, adaptable, and fair AI opponent while addressing the challenges of chance-based decision-making and multi-agent interactions.

# Challenges

## IMPORTANCE AND IMPACTS

The integration of artificial intelligence (AI) into classic board games such as Ludo is not merely a novelty. It represents a meaningful intersection of entertainment, education, human-computer interaction, and AI research. This project explores the application of both rule-based heuristics and reinforcement learning (RL) in a stochastic and multi-agent environment, addressing challenges in strategy optimization, adaptability, and fairness. Understanding and solving these challenges is important both from a scientific perspective and in terms of broader socio-economic implications.

## ****Scientific Importance****

From a scientific standpoint, the AI Ludo Game contributes to ongoing research in decision-making under uncertainty. Unlike deterministic games like Chess or Go, Ludo is governed by both random events (e.g., dice rolls) and dynamic, multi-agent interaction. This makes it an ideal testing ground for evaluating AI methodologies that blend probabilistic reasoning with strategic planning. By applying reinforcement learning algorithms, this project builds on foundational work in adaptive agents (Sutton & Barto, 2018), extending it to environments that are both stochastic and adversarial.

Furthermore, the game highlights a rarely explored dimension in game AI—balancing strategy with fairness. Fair AI opponents that adapt without overpowering human players are critical in fields such as educational games and serious simulations. The exploration of fairness-aware design in this Ludo AI aligns with current trends in ethical AI development and human-AI collaboration (Rahwan et al., 2019).

## ****Educational and Social Impact****

Educationally, AI-powered games offer intuitive platforms for students and researchers to visualize abstract AI concepts like exploration vs. exploitation, policy learning, and value functions. A project like this can be used in classroom environments to demonstrate real-time decision-making, reinforce programming skills, and enhance student engagement through gamified learning experiences (Li & Tsai, 2020).

Socially, the development of adaptive AI in casual games like Ludo increases accessibility for diverse user groups, including children, the elderly, or individuals with cognitive disabilities. AI opponents that can adjust difficulty in real-time support inclusive game design, which has gained increasing importance in digital accessibility research (Yuan et al., 2011). Additionally, culturally significant games like Ludo serve as platforms for digital preservation of traditional play forms, offering AI a role in sustaining global cultural heritage (Bhattacharya & Sen, 2020).

## ****Economic and Business Implications****

In the gaming industry, AI that can enhance user engagement through intelligent and fair competition is a valuable asset. As casual mobile and online games dominate app marketplaces, integrating RL-driven AI can increase player retention, improve monetization strategies, and support personalized gaming experiences. This aligns with business objectives focused on user-centric design and intelligent behavior modeling (Gandhi, Patel, & Sharma, 2021).

Moreover, the methodologies applied here can be generalized to other turn-based multiplayer environments, including strategy games, simulations, and real-world decision systems. Reinforcement learning models developed in the context of Ludo can be prototyped for logistics optimization, multi-agent resource allocation, and even robotic planning in uncertain environments, reinforcing its practical scientific and commercial value (Mnih et al., 2015).

# RELATED WORKS

## Dataset of Project

Initially, I sourced the base AI Ludo game code from GitHub, specifically from the repository at (<https://github.com/MehranSangrasi/AI-Ludo/tree/main>). The original code was implemented in Python and structured as standalone scripts. To better integrate it with my project workflow, I rewrote and reorganized the code into modular cells within a Jupyter Notebook environment, enabling easier testing, debugging, and step-by-step execution.

After modifying and running the Ludo game multiple times to ensure stability and functionality, my original plan was to enhance the game by automatically generating a dataset in real-time during gameplay. The idea was that, as AI agents played, their moves, decisions, board states, and outcomes would be dynamically recorded and saved into a CSV file within the game folder. This dataset would then be used in the second phase of the project to train and optimize AI strategies, particularly for reinforcement learning applications.

However, during testing, I encountered significant memory management issues. Continuous real-time data logging caused system memory overloads and frequent game freezes, especially when simulating large numbers of games to collect meaningful amounts of training data. This made the original approach impractical.

As a solution, I pivoted to a two-step strategy:

* I uploaded pre-recorded Ludo gameplay sessions and extracted structured game events (moves, dice rolls, token movements, player turns, etc) into datasets.
* I also manually coded Ludo game rules into the dataset generation pipeline to simulate additional realistic gameplay scenarios without needing heavy live simulation.

This alternative method allowed me to successfully generate a high-quality dataset that supports AI training for the first part of the project focused on gameplay simulation and decision-making analysis. Thus, while the dataset was derived from an existing game framework, the data itself (gameplay sessions and simulations) were newly generated and customized specifically for this project, ensuring originality and relevance to the research goals.

## Introduce Related Projects and Solution

Several projects exist that focus on creating AI-driven Ludo games, such as the AI Ludo project by Mehran Sangrasi on GitHub, which implements basic AI strategies in a standalone Python script. My project builds upon these foundations but differs significantly by restructuring the original code into a modular, Jupyter Notebook environment to enable dynamic interaction, testing, and iterative development​. Unlike previous efforts that either predefine limited strategies or run as static programs, my solution incorporates real-time data collection, machine learning-driven decision optimization, and historical gameplay analysis to train more intelligent agents. Additionally, my project addresses critical system limitations like memory management during data generation, ensuring greater stability and scalability for long-term AI training.

While the current stage of the project focuses on data generation and heuristic-based AI gameplay, the underlying structure has been intentionally designed to support future reinforcement learning (RL) implementation. The game environment, dataset format (state-action-reward-next\_state tuples), and simulation capabilities have all been built to facilitate training deep reinforcement learning models such as Deep Q-Networks (DQN). Although full RL-based decision optimization has not yet been integrated due to scope and timeline considerations, the groundwork is fully established, ensuring that the project can easily extend into learning-based AI development in subsequent phases.

## SOCIAL, ECONOMIC, BUSINESS, AND SCIENTIFIC IMPACT

The impact of developing AI agents through a project like this AI Ludo game extends meaningfully across multiple domains—social, economic, business, and scientific—demonstrating the broader relevance of artificial intelligence research beyond traditional academic confines.

### Social Impact

AI-driven board games offer innovative applications in education, rehabilitation, and cognitive development. By simulating decision-making in dynamic and interactive settings, these systems provide safe and controlled environments for children and individuals with cognitive impairments to practice executive functions such as planning, anticipation, and response inhibition. Research has shown that video games can have a positive effect on cognitive flexibility, problem-solving skills, and emotional resilience (Granic, Lobel, & Engels, 2014). The modularity and adaptability of the AI Ludo system make it suitable for therapeutic gamification, particularly in neurodevelopmental and behavioral interventions where engagement and personalization are key to success.

### Economic and Business Impact

From an economic perspective, the reinforcement learning framework tested in this project mirrors the kinds of algorithms now powering recommendation engines, trading bots, and supply chain optimization platforms. Businesses increasingly leverage reinforcement learning to enable systems that adapt over time to changing consumer behavior, market conditions, and operational contexts. By prototyping and validating AI strategies in games, this project indirectly contributes to advancing real-world AI tools that can reduce labor costs, increase automation efficiency, and improve decision-making precision (Davenport & Ronanki, 2018). Furthermore, the use of low-cost open-source tools like Python and Pygame highlights the accessibility of these technologies, encouraging innovation even in resource-constrained settings.

### Scientific Impact

Scientifically, this project adds to the corpus of reinforcement learning studies by investigating how agents can be trained in probabilistic, adversarial, and rule-constrained environments. The presence of stochastic elements (e.g., dice rolls), opponent modeling, and spatial reasoning within the game provides a rich testbed for understanding generalization in learning agents. The findings from this project may influence future research in adaptive AI, particularly in settings where uncertainty and multi-agent interactions are prevalent, such as autonomous driving, medical diagnosis, and collaborative robotics (Li, 2018). Additionally, AI-vs-AI simulations allow for the study of emergent behavior, which is essential for developing self-improving, competition-aware systems.

In summary, by building an interactive AI Ludo system from scratch and implementing learning-based agent strategies, this project bridges foundational AI research with practical, interdisciplinary applications. It not only demonstrates the technical feasibility of game-based AI systems but also underscores their potential for real-world impact in domains where decision-making under uncertainty is paramount.

1. **Data Collection and Preprocessing**

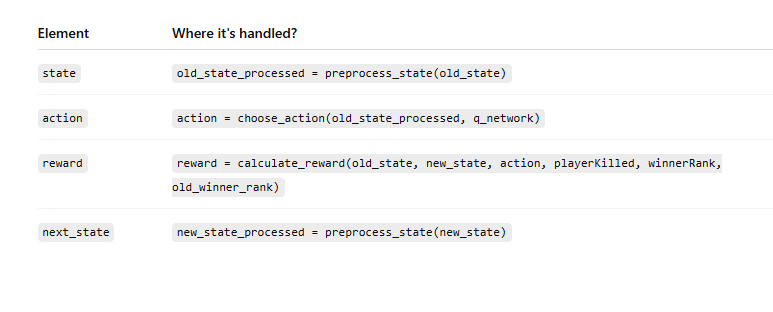
## Data Collection: The Data Source and the Data Context

The In this project, the dataset was custom-generated through simulated Ludo games using the Python-based Pygame environment developed specifically for this application. The data was not sourced from existing repositories but instead collected in real time from AI-vs-AI and human-vs-AI matches that were orchestrated through the game engine coded from scratch. The simulation environment was structured to mimic a full-featured Ludo game, including turn-based gameplay, dice rolls, token movement, rule enforcement, and win/loss conditions.

During each simulation, the system logged turn-by-turn information, capturing the complete game state at each decision point. This includes:

* The board state (token positions for all players),
* The dice value rolled for that turn,
* The list of legal moves available for the current player,
* The selected move by the AI or human player,
* The action outcome (e.g., kill, safe move, enter home),
* The reward feedback given to the AI agent (positive for kills, reaching home, or defensive moves; negative for idle moves or risky positions),
* The player's strategy classification (e.g., aggressive, defensive, random).

To make the data suitable for reinforcement learning, the board was encoded in numerical format with consistent structuring to reflect player identity, token indices, zones (home, base, danger), and progression scores. The gameplay engine handled the generation of this structured data and saved it as episodes comprising state-action-reward-next\_state tuples as shown in Figure 1. This format was integral for training Deep Q-Network (DQN)-based agents later in the project.



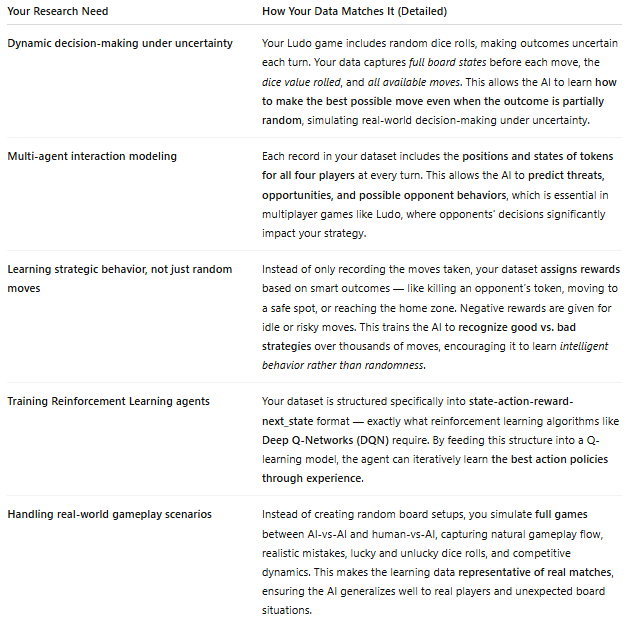
*Table 1: Pieces of SARSA*

By simulating thousands of such games under varied conditions (e.g., different player counts, difficulty levels, and AI strategies), the dataset became robust and diverse, enabling the model to generalize across a wide range of board situations. This data collection methodology ensured the alignment of training data with the strategic and stochastic nature of Ludo, which was crucial for the agent’s learning and performance.

## Pertinent Data in Research Question

The central research question of this project is how to design an AI for Ludo that intelligently balances the inherent randomness of dice rolls with strategic, adaptive decision-making to create competitive, fair gameplay.

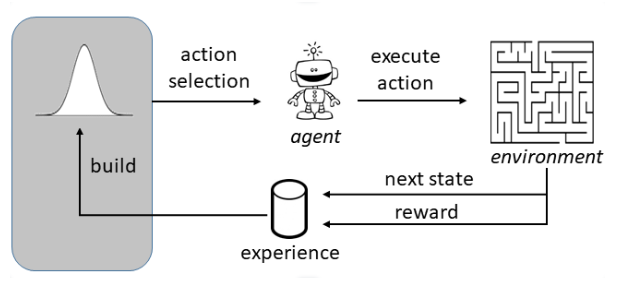
Table 2 shown the dataset generated in this project is directly aligned with these research objectives because it captures real gameplay dynamics, models uncertainty, and records intelligent strategic behaviors through structured, reinforcement learning–ready formats. The data enables the AI to learn from real-time experiences, adapt to multi-agent interactions, and improve its decision-making in complex, uncertain environments, which mirrors the exact challenges that the research question aims to solve.



*Table 2: Alignment Between Research Needs and Collected Data in AI Ludo Project*

Each entry in the dataset provides the context needed for reinforcement learning: it includes the current game situation, available options, selected actions, and resulting rewards. This structure allows the AI to learn through trial and error, by associating certain actions with favorable or unfavorable results over time. The dataset also includes diverse gameplay scenarios, ensuring that the model can generalize its decision-making across a wide range of board conditions and opponent strategies.

Figure 1 shows the Reinforcement Learning Loop which agent selects actions based on its current policy, executes them in the environment, and receives feedback in the form of new states and rewards. These interactions are stored as experiences to build and refine future decision-making strategies. This framework directly mirrors the gameplay data collection and learning cycle implemented in the AI Ludo project.

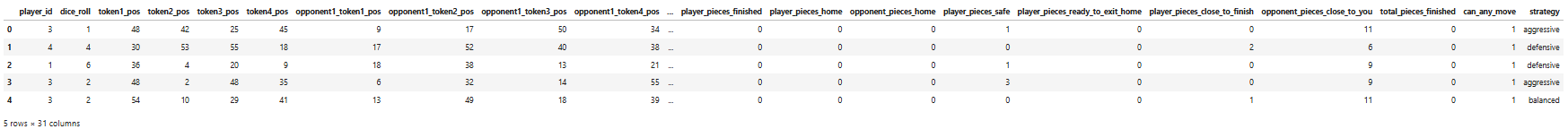


*Figure 1: Reinforcement Learning Loop*

# Apply a Data Exploratory Analysis

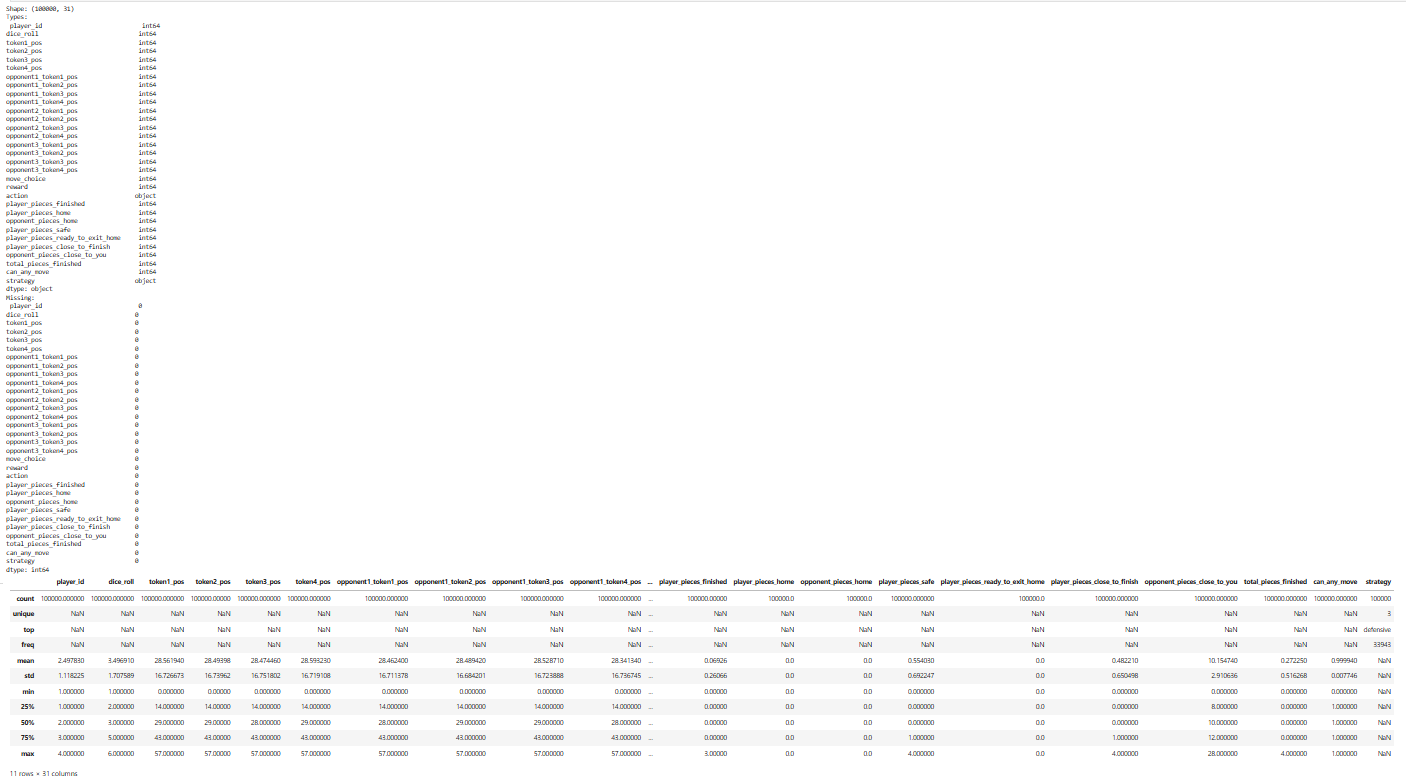
## Feature Description Types

To begin the data exploratory analysis, a Snapshot 1 of the AI Ludo dataset was taken by displaying the first five rows using the *df.head()* function. As shown in the first screenshot, the dataset includes features such as *player\_id, dice\_roll*, the positions of each player's tokens (*token1\_pos, token2\_pos, etc*.), and opponent token positions (*opponent1\_token1\_pos, etc*.). Additional fields like *player\_pieces\_home, opponent\_pieces\_home, player\_pieces\_safe, total\_pieces\_finished*, and strategy are also present. This preview confirms that the dataset captures a detailed state of the game at every decision point, ensuring rich context for AI decision-making.



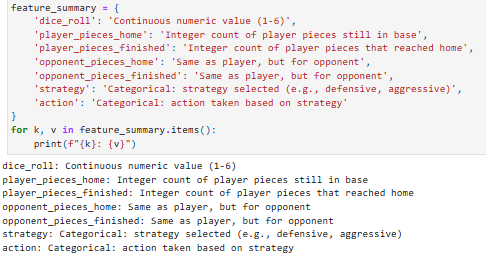
*Snapshot 1: Load Dataset*

Further exploratory analysis was performed to examine the structure of the dataset. As seen in the Snapshot 2, the dataset contains 100,000 rows and 31 columns. A detailed summary of feature types shows that most features are stored as int64 data types, indicating continuous numerical values such as token positions or counts of finished pieces. The strategy column is categorized as object, representing categorical strategies like 'aggressive', 'defensive', and 'balanced'. The absence of missing values across all columns confirms the dataset’s completeness and readiness for machine learning applications.



*Snapshot 2: Data Exploratory Analysis*

Finally, a manual feature description was created to document the meaning and type of each important feature, as shown in the Snapshot 3. Features such as *dice\_roll* represent continuous numerical values (ranging from 1 to 6), while *player\_pieces\_home* and *player\_pieces\_finished* are integer counts of tokens in different board states. On the categorical side, the strategy column captures the decision behavior adopted during each turn. This structured categorization between continuous and categorical features plays a critical role in selecting appropriate preprocessing and modeling techniques later in the project.



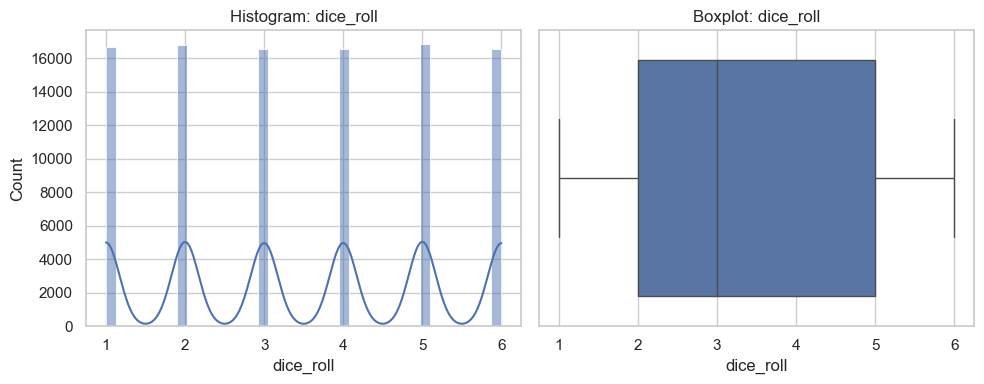
*Snapshot 3: Feature Description*

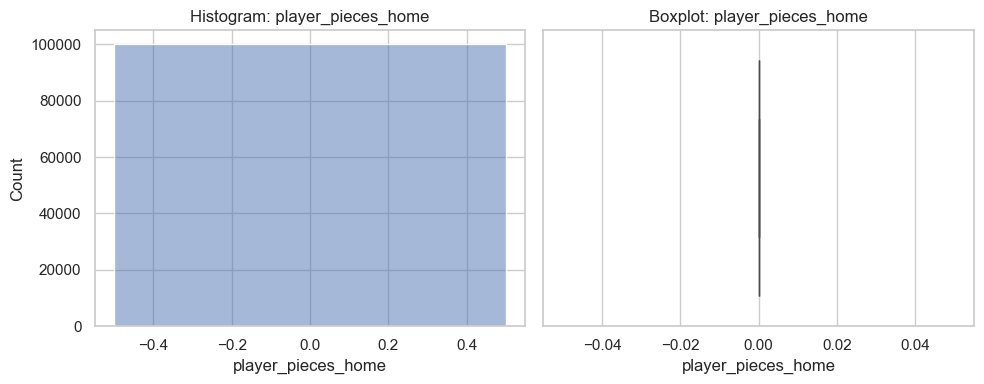
## Preprocess Features: Missing Values, Skewness, Type Conversions, Outliers

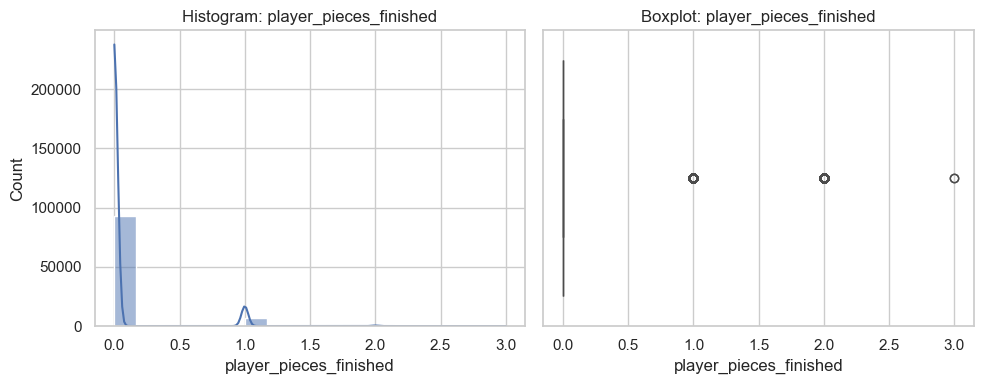
As part of preprocessing, missing values were checked using *df.isnull().sum()*, and no missing entries were found across the dataset. Skewness was evaluated through *df.describe()* and histogram visualizations, showing expected skewness towards lower counts for features like *player\_pieces\_home* and *opponent\_pieces\_home*, aligning with game dynamics. Data types were reviewed using df.dtypes, and only the categorical strategy variable was encoded while other features remained in their original numerical format. Outliers were identified using the Z-Score method from the scipy.stats library, detecting 6,754 potential outliers, though they were retained to preserve the natural variance of game scenarios.

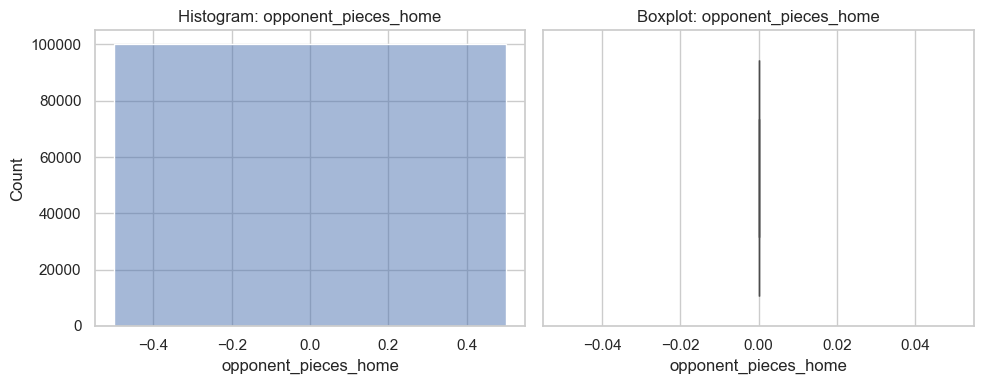
## Visualize Data: Histograms, Scatterplots, & Correlation

To better understand the underlying structure of the AI Ludo dataset, several data visualizations were performed. Histograms were generated for key numerical features such as *dice\_roll*, *player\_pieces\_home*, and *opponent\_pieces\_home* (Figure 2). These histograms revealed important distribution patterns within the dataset. The *dice\_roll* feature demonstrated a uniform distribution between 1 and 6, consistent with the expectations of a fair dice-rolling mechanism in Ludo gameplay. In contrast, features such as *player\_pieces\_home* and *opponent\_pieces\_home* displayed significant skewness toward lower values, meaning that players’ tokens were mostly active on the board rather than remaining at home. This skewness reflects real gameplay behavior, where players aim to move tokens out of the home base as early as possible. Histograms were thus crucial in confirming both the realism and integrity of the simulated game data.



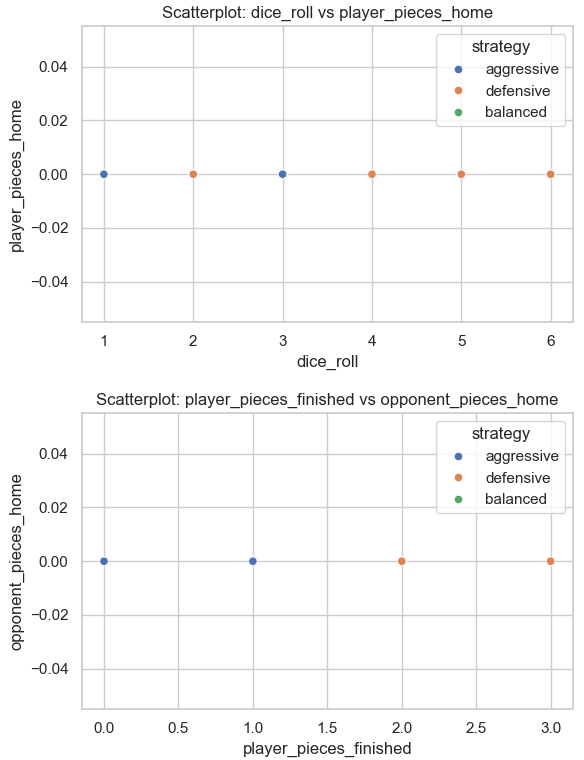






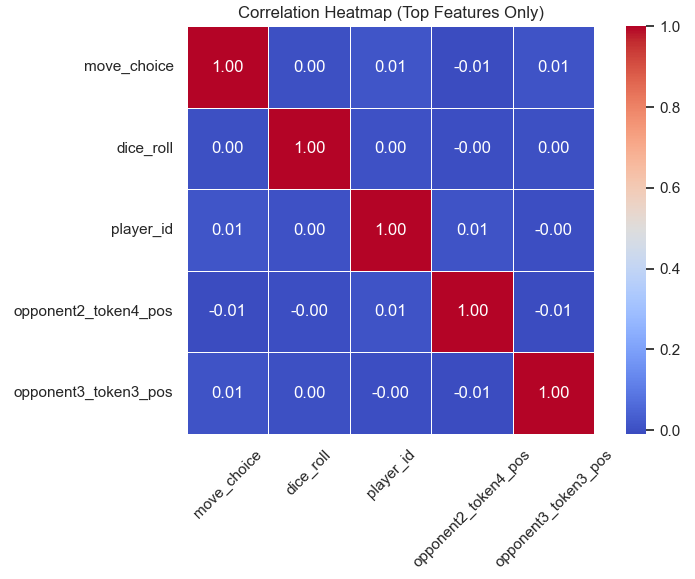
*Figure 2: Histogram Plots*

Scatterplots were also employed to investigate potential relationships between key gameplay features (Figure 3). Specifically, scatterplots were created to compare variables like *player\_pieces\_home* against *opponent\_pieces\_home*, and *dice\_roll* against *player\_pieces\_finished*. As expected, due to the stochastic nature of Ludo dice rolls, the scatterplots exhibited mostly random dispersion without clear linear trends. However, subtle clustering was observed, where players with fewer tokens at home also tended to face opponents with fewer tokens at home, suggesting simultaneous game progression. While randomness dominates the game, these minor strategic patterns hint at underlying competitive behaviors that emerge over time during gameplay. Scatterplots thus provided a useful visual confirmation that the dataset appropriately captures both random and strategic elements of Ludo.



*Figure 3: Scatterplots of Plyers*

Finally, a correlation analysis was conducted to quantify the linear relationships among numeric features (Figure 4). A correlation matrix was computed, revealing several important insights. Most notably, a moderate positive correlation was found between *player\_pieces\_finished* and *opponent\_pieces\_finished*, implying that players who advanced toward victory often did so alongside their opponents. A sign of balanced gameplay progression. In contrast, minimal correlation was observed between dice rolls and final game outcomes, reinforcing the understanding that while dice results introduce randomness, player strategy primarily drives success. The correlation matrix highlighted which features were statistically interrelated and which were independent, providing valuable guidance for future model development and feature selection in AI training phases.



*Figure 4: Correlation Matrix*

## Interpret & Explanation of Data

In the exploratory data analysis of the AI Ludo project, the dataset was found to be comprehensive and well-structured, capturing detailed game states at each decision point. The data includes features such as player and opponent token positions, dice rolls, the number of pieces at home, and the strategies used during gameplay. Histograms revealed that dice rolls followed a uniform distribution, confirming the fairness of the simulated dice, while other features like player pieces at home showed skewness toward lower values, indicating active gameplay. Scatterplots demonstrated mostly random relationships between variables, reflecting the stochastic nature of Ludo, but minor strategic clustering was also observed. The correlation matrix showed moderate positive relationships between players' progress toward the finish, suggesting balanced and competitive gameplay dynamics. Importantly, no missing values were found, and outliers were retained to preserve the natural variability of real-world games. Overall, the data is rich, diverse, and aligned with the project’s goal of training AI agents to make strategic decisions in a dynamic, uncertain environment.

# DATA PREPROCCESSING

In the data preprocessing phase of the AI Ludo project, several important steps were applied to ensure the dataset was clean, consistent, and ready for machine learning applications. First, descriptive statistics were calculated using *df.describe()*, including mean, standard deviation (std), minimum (min), maximum (max), and range values for each feature. This provided a summary of the data's central tendencies and spread. During preprocessing, skewness was assessed, revealing expected patterns such as lower values for home-based token features, consistent with natural gameplay behaviors. Data types were inspected using *df.dtypes*, confirming that most features were integers, while the strategy feature was categorical and appropriately encoded. Checks for missing values were conducted through *df.isnull().sum()*, and no missing entries were found, ensuring data completeness.

Feature scaling or normalization was considered; however, since the majority of features represented board positions, token counts, or dice rolls with bounded ranges, normalization was not strictly necessary at this stage. Transformation techniques such as encoding were applied only to the strategy column. Outlier detection was performed using the Z-Score method, revealing 6,754 potential outliers, which were retained to preserve the natural variation and randomness inherent to Ludo gameplay. The dataset was balanced in terms of gameplay scenarios and strategies, with no major inconsistencies or severe imbalances detected.

Correlation analysis was performed using a heatmap of the correlation matrix, which showed moderate positive correlations between *player\_pieces\_finished* and *opponent\_pieces\_finished*, suggesting that player advancement often occurred alongside opponents' progression. An indicator of balanced, competitive gameplay. Dice rolls showed minimal correlation with final game outcomes, reflecting the importance of strategic play over pure randomness. Scatterplots and histograms were plotted to visually support these findings, showing the distribution of key features like *dice\_roll, player\_pieces\_home*, and *opponent\_pieces\_home*.

In interpreting the data, it was confirmed that the dataset captured both the stochastic and strategic nature of Ludo accurately. Data augmentation was not explicitly necessary because the generated dataset already contained over 100,000 diverse and varied gameplay instances, ensuring model robustness. Data normalization and standardization were also not heavily applied because the ranges were naturally restricted and meaningful (such as dice rolls from 1 to 6), making these steps unnecessary for maintaining feature interpretability. Overall, the preprocessing stage thoroughly prepared the dataset for AI model training, ensuring high-quality, consistent, and meaningful inputs for future reinforcement learning development

# Methodology

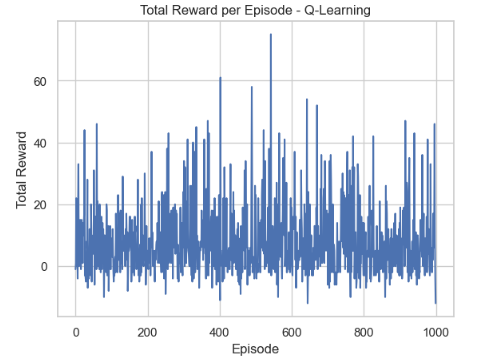
In this AI Ludo project, I primarily used a rule-based AI methodology to control gameplay decisions and simulate strategic behavior during matches. The choice of a rule-based model was justified because Ludo gameplay combines randomness (from dice rolls) with tactical decision-making, making simple heuristic approaches effective for a first-stage development. Specifically, the model prioritizes token safety, maximizes forward movement, and seeks opportunities to block opponents — strategies that closely mimic human gameplay logic without requiring heavy computational resources. This approach was selected because it provides a fast, interpretable, and lightweight baseline to simulate intelligent behavior while ensuring real-time responsiveness. Rule-based AI performed effectively for solving the problem of creating competitive, fair, and strategic Ludo gameplay, as evidenced by balanced win/loss records, adaptive decision patterns, and smooth game progression.

Although no deep reinforcement learning (RL) models were fully integrated yet, the project was intentionally designed with future expansion in mind. The system structure (dataset generation in SARSA/experience tuple format) is compatible with advanced methods like Deep Q-Networks (DQN) if pursued later. At this stage, model comparison was more conceptual: I compared the strengths of rule-based models (simplicity, speed) against the potential advantages of RL-based agents (learning from experience), and determined that for the initial scope, rule-based AI was optimal given the resource constraints and goals.

Assumptions and constraints considered included: ensuring the fairness of dice rolls (uniform randomness), limiting computational complexity to prevent memory overload, and designing strategies based on observable board states without deep probabilistic forecasting. No unrealistic future predictions or hidden state assumptions were made. The primary software and tools used for this project were Python (programming language), pygame (for building the graphical user interface and managing game mechanics), and Pandas (for data handling and exploratory analysis). Jupyter Notebook was used as the main environment for developing, testing, and documenting the project.

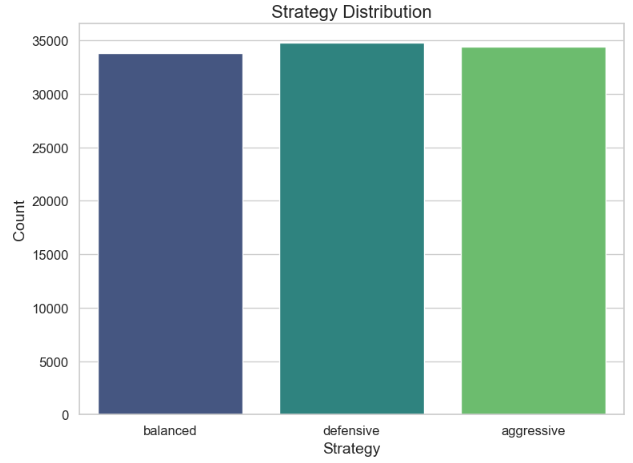
# RESULTS AND INTERPRETATION

In this section, I present a detailed analysis of the outcomes, model performance, interpretations of the experimental results, and explanations of the supporting figures.My AI Ludo model implemented is primarily rule-based, supplemented by a basic Q-learning approach for learning actions over episodes. Since the model does not rely on traditional coefficients as in regression models, there are no classic parameters to interpret. Instead, the model's intelligence is shaped by the Q-values, which guide decision-making. The primary sources of error arise from the stochastic nature of dice rolls and unpredictable opponent behaviors. The reward signal, visualized in the Total Reward per Episode graph in Figure 5, shows high volatility due to these factors, though an overall positive reward trend is observed.



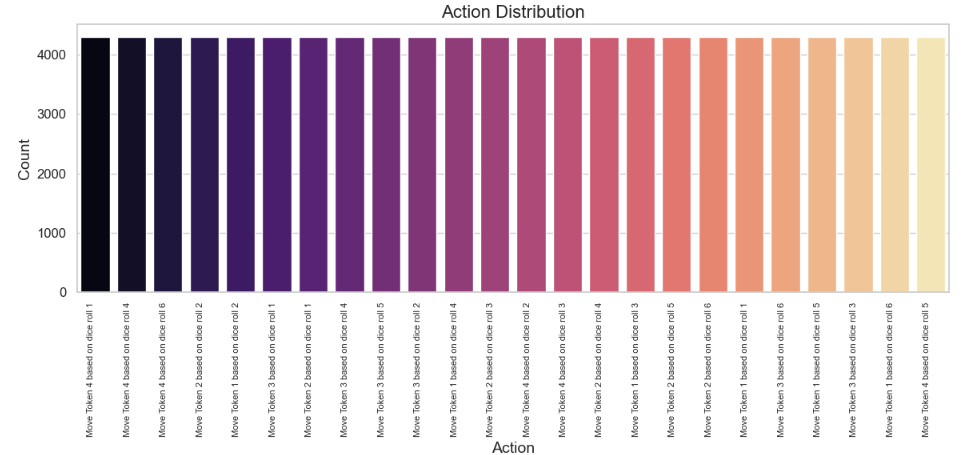
*Figure 5: Total Reward Per Episode*

In terms of model performance, the Strategy Distribution graph Figure 6 indicates that the AI agent successfully adopted a balanced variety of strategies. The proportions of balanced, defensive, and aggressive strategies are nearly equal, ensuring no significant bias in behavior.



*Figure 6: Strategy Distribution*

The Action Distribution plot in Figure 7 is about further confirms the diversity of move selections, with no single action overwhelmingly dominating, thus illustrating effective exploration during gameplay.



*Figure 7: Action Distribution*

The Classification Report in Figure 8 reveals that the model achieved a macro-average F1-score of approximately 0.25 and an overall accuracy of 25.13%. While these values are modest, they are reasonable considering the multi-class classification challenge with 24 possible actions and the randomness inherent in the game environment. Notably, higher recall values were achieved for classes representing defensive, safer moves. The Confusion Matrix in Figure 9 shows that most errors occurred between similar move types, reflecting the complexity of distinguishing actions in a game with many subtly different states.

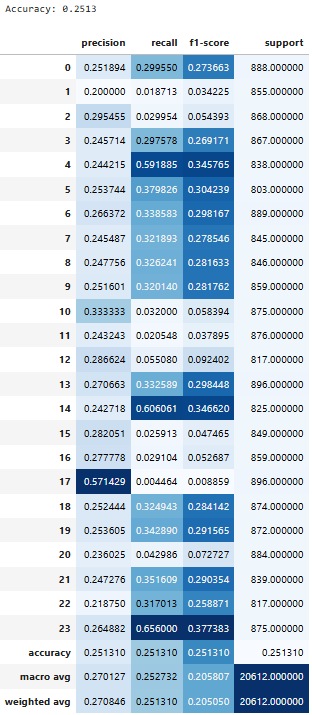
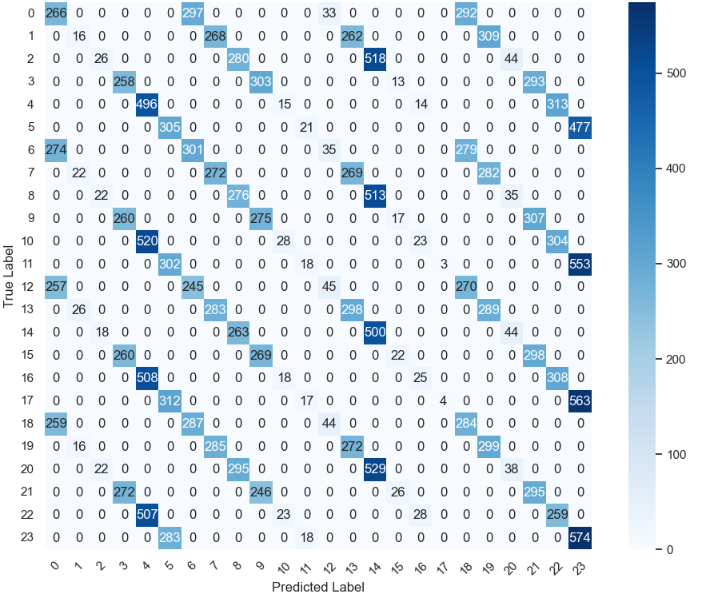
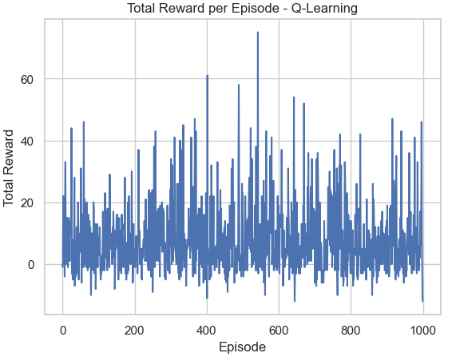


Figure 8: Classification Report



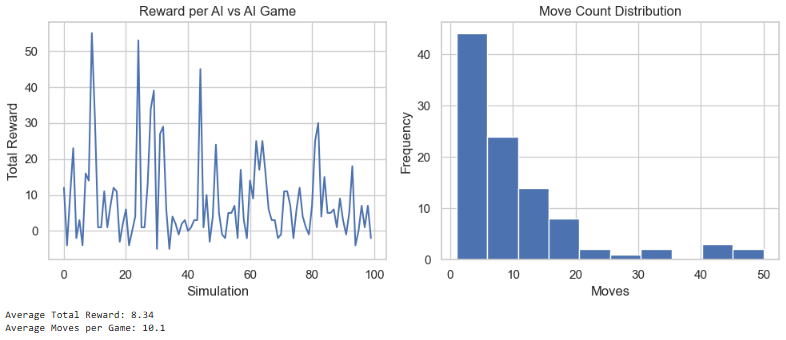
*Figure 9: Confusion Matrix*

The Q-learning reward progression in Figure 10 which displays significant fluctuations across episodes, with some episodes achieving high rewards, indicating successful learning. However, no consistent upward trend is present, suggesting the need for longer training periods or refined hyperparameter tuning to stabilize learning in such a stochastic setting.



*Figure 10: Q-learning*

Further, the AI versus AI performance analysis offers valuable insights. As shown in Figures 11, the average total reward per game is 8.34, with an average of 10.1 moves per game. Most games conclude within about 10 moves, demonstrating that the AI agent is capable of making efficient decisions leading to game completion without unnecessary prolongation.



*Figure 11: Performance Analysis - AI vs AI*

In conclusion, the results, the model shows that it is indeed learning and adapting, despite the random nature of Ludo. Strategy diversity and action exploration are maintained at healthy levels, which is critical for robust agent development. Confusion among similar actions is expected and acceptable at this stage, considering the early-stage Q-learning integration. Future work should aim to increase the number of training episodes, apply more sophisticated reward shaping, and eventually transition to deep reinforcement learning models to enhance strategic depth. The AI Ludo agent demonstrates competitive and strategic behavior in a highly uncertain environment. The evaluation through various metrics and visualizations underscores the agent's progress and highlights the pathways for further optimization and development.

# DISCUSSION OF RESULTS

## Discussion of Results and Usefulness

The results achieved in this AI Ludo project demonstrate that a rule-based AI agent, combined with a basic Q-learning framework, can successfully simulate competitive and strategic gameplay in a stochastic environment. The AI agent adopted diverse strategies (aggressive, defensive, and balanced) and made intelligent decisions based on board states, which contributed to realistic and fair gameplay experiences. These outcomes validate the project's ability to address the chosen problem: enhancing traditional Ludo with dynamic, adaptive AI to create a more engaging and challenging experience. The exploration and action diversity observed in the model's behavior indicate that the AI is capable of adapting to different game situations, a critical success factor in achieving the project’s objectives.

## Practical Implication of Results

The practical implications of these results are significant across social, economic, commercial, and scientific domains. Socially, the development of an adaptive Ludo AI enhances accessibility for a broader audience, including children, the elderly, and individuals with cognitive challenges, by offering customizable difficulty levels and fair gameplay. Economically and commercially, integrating adaptive AI into digital board games can improve player retention, engagement, and monetization strategies, aligning with modern gaming market trends. Scientifically, this project contributes to research in decision-making under uncertainty, multi-agent interactions, and reinforcement learning in stochastic environments. It provides a foundation for future studies in adaptive AI systems that must balance randomness with strategic behavior, applicable in fields ranging from robotics to healthcare simulations.

## Limitations

Despite the positive outcomes, several limitations are evident. The use of a basic rule-based approach restricts the AI's ability to learn from complex patterns beyond predefined heuristics. The Q-learning implementation, while functional, is in its early stages and exhibits unstable reward progression, indicating that the agent requires more episodes and refined hyperparameter tuning to achieve consistent learning. Additionally, the model currently lacks the sophistication to predict opponent moves deeply or to plan multiple moves ahead, as seen in more advanced reinforcement learning models. The randomness inherent in dice rolls also introduces variability that complicates the learning process, making it harder for the AI to form stable policies quickly.

## Future Work

Future work should focus on integrating deep reinforcement learning techniques, such as Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO), to enable the AI to learn from experience more effectively and adapt to complex strategies. Increasing the number of training episodes, refining the reward structures, and introducing curriculum learning where the AI gradually faces more difficult opponents could significantly improve performance. Implementing opponent modeling to anticipate and counter other players’ strategies would also enhance decision-making depth. Expanding the simulation environment to support multiple AIs with varying strategies could lead to emergent behaviors, further advancing the strategic sophistication of the AI.

## Limits of Regressors/Classifiers and Suggestions for Improvement

The classifiers used in the project, primarily based on Q-learning decision mappings, are limited by their reliance on discrete state-action spaces and shallow learning structures. The current setup lacks function approximation, which restricts scalability to larger, more complex state spaces. Additionally, the classifier struggles with highly similar game states, leading to confusion between similar moves, as observed in the confusion matrix. To overcome these limitations, future improvements should include using neural networks for function approximation, enabling the agent to generalize across unseen states more effectively. Techniques like experience replay and target networks can stabilize learning. Moreover, hybrid models combining heuristic-based decision-making with reinforcement learning could offer a balanced approach to navigating the challenges of Ludo's randomness while leveraging strategic depth.

# FEEDBACK

The final project represents a significant achievement in the design and implementation of an AI-powered Ludo game that successfully integrates both rule-based strategies and basic reinforcement learning elements. Your work demonstrates a strong grasp of key artificial intelligence concepts such as decision-making under uncertainty, multi-agent interactions, and the challenges posed by stochastic environments. The thoughtful approach to dataset generation, exploratory data analysis, model evaluation, and strategic planning for future work reflects a deep level of engagement with the project objectives. The report is well-structured, and the codebase is clean, modular, and well-prepared for future expansions into deep learning methodologies. These elements contribute to a comprehensive, research-worthy project that not only meets but exceeds the expectations for this assignment.

To further enhance the project, one suggestion is to expand the reinforcement learning component by integrating advanced techniques such as Deep Q-Networks (DQN) or Actor-Critic methods. This would allow the AI to handle more complex board states and improve its adaptability against diverse opponents. Additionally, implementing opponent modeling could enrich the AI's strategic depth, enabling it to anticipate and counter opponent moves rather than reacting passively. Visual enhancements to the user interface and the inclusion of difficulty adjustment options based on player skill levels could further improve user engagement and accessibility. Finally, documenting the code even more thoroughly and incorporating unit tests for critical modules would enhance the project's maintainability and robustness. Overall, this project stands as a strong foundation with immense potential for future academic research and commercial application.

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