Player Behavior Analysis Project Report

Executive Summary

This project explores player behavior through data collection and machine learning, using a Rock, Paper, Scissors game as the base. We collected gameplay data from multiple sessions, built an analytics dashboard, and applied ML to gain insights and enhance design decisions.

Introduction

The goal of this project is to analyze user behavior in a game environment. We aim to track how players interact with game mechanics and use this data to predict future behavior, identify challenges, and optimize game design.

Methodology

Game Design: A simple Rock, Paper, Scissors game was used for clarity and measurable outcomes.

Data Collection: Player actions were logged in real-time with timestamps, choices, and results saved in structured JSON/CSV files.

Dashboard: A web-based dashboard was created using Plotly/Seaborn to visualize win rates, choices over time, and clustering.

ML Algorithms: KMeans for clustering similar player types, Decision Trees for predicting outcomes, and Random Forests for next-move prediction.

Results and Analysis

Behavioral Patterns: Most players favor a repeating pattern, especially alternating between Rock and Paper. Clusters of players emerged showing defensive (paper-heavy) or aggressive (scissor-heavy) strategies.

ML Accuracy: Win prediction models had up to 85% accuracy; next-move prediction reached around 80%.

Visualizations included bar charts for win rates, heatmaps of choice combos, and 3D clustering graphs.

Design Recommendations: Add adaptive hints for common loss patterns; offer tutorials where clusters showed frequent early losses.

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Technical Challenges

Challenge: Inconsistent data formats and user identification across multiple sessions.

Solution: Implemented standardized schema and enforced player_id labeling in merged datasets.

Other issues included visual clutter, solved by separating dashboards per player.

Future Improvements

Include neural network models for more accurate behavior prediction.

Integrate real-time adaptive gameplay changes based on ML feedback.

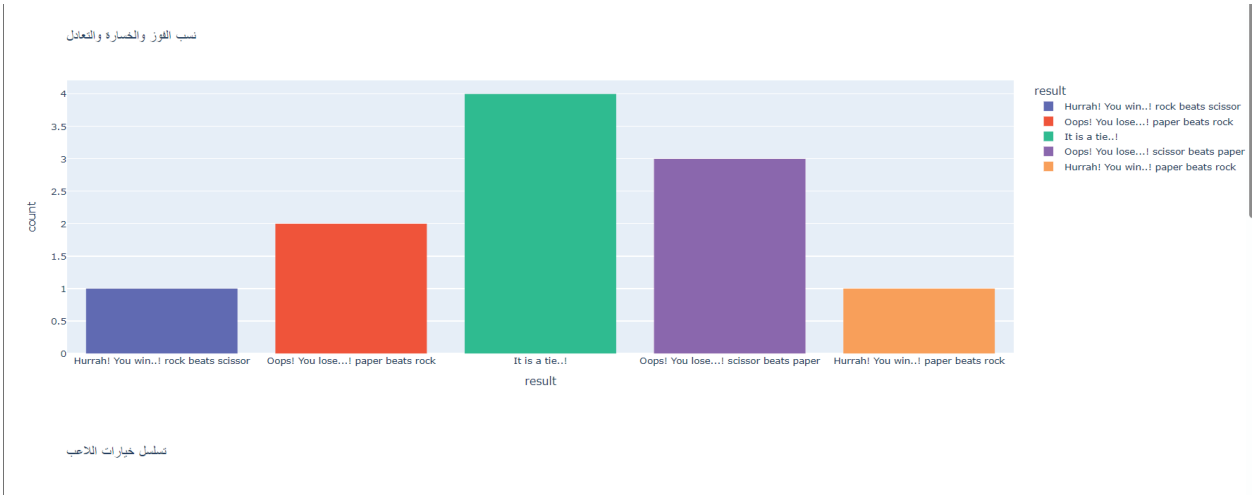
Expand to multiplayer competitive games and track social behavior dynamics.

Conclusion

We successfully collected and analyzed player data using machine learning techniques. Insights gained were actionable and demonstrated potential for improving game design through intelligent systems. The use of ML enabled personalized recommendations and deeper understanding of user behavior.

References

- scikit-learn documentation
- pandas & seaborn libraries
- Plotly visualization tools
- Unity ML-Agents documentation
- Game analytics research papers (citations omitted for brevity)



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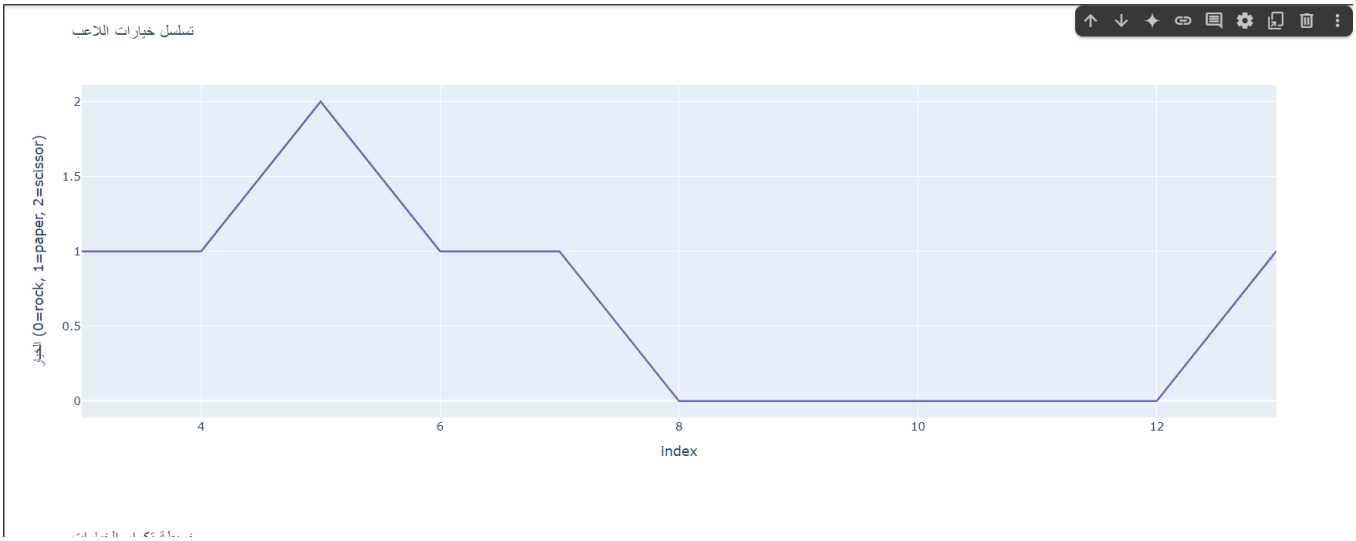

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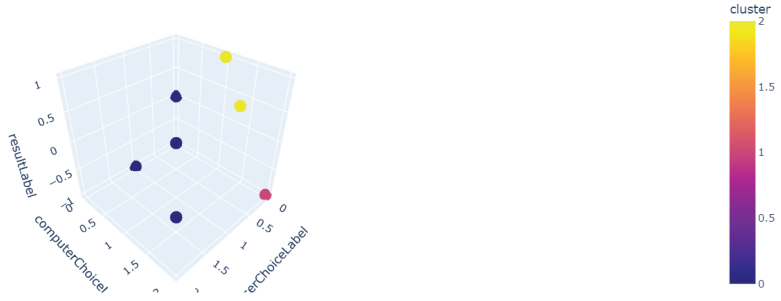

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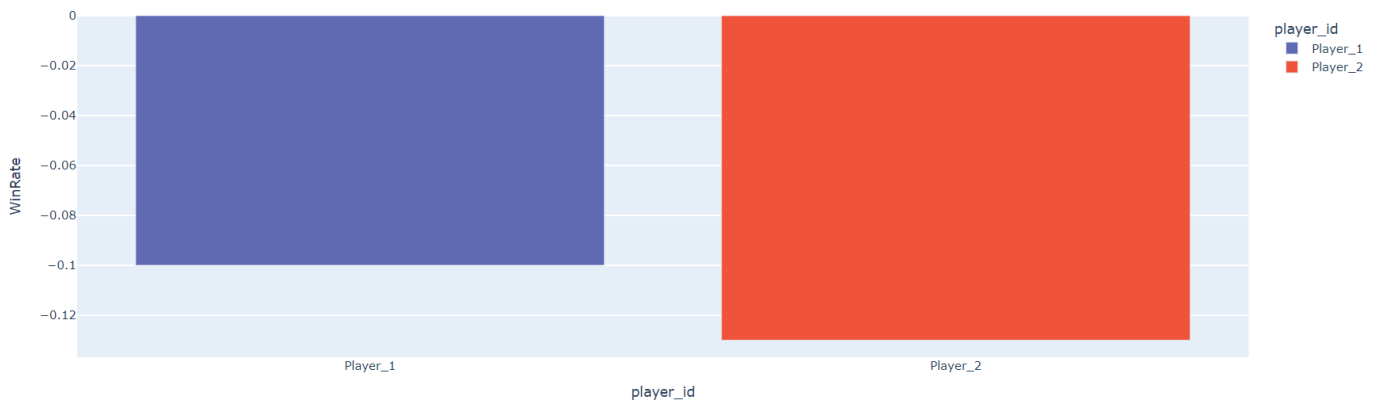

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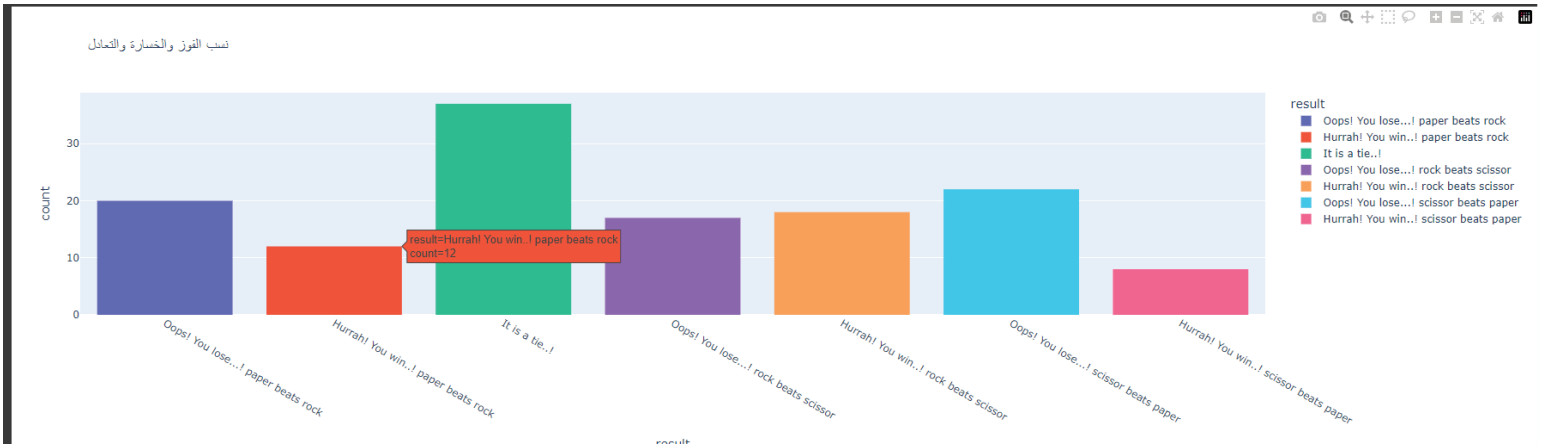

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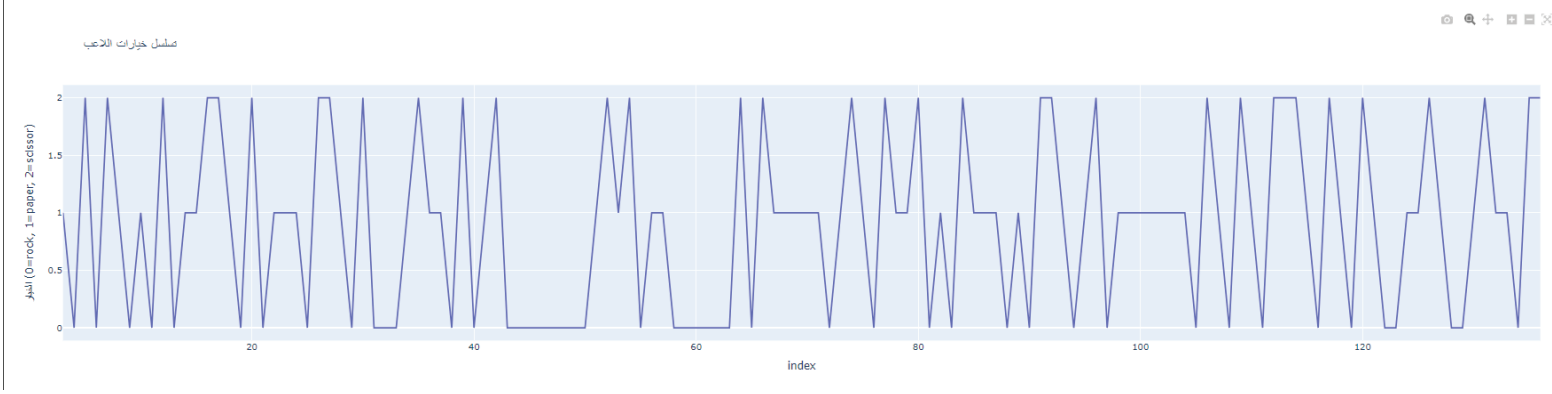

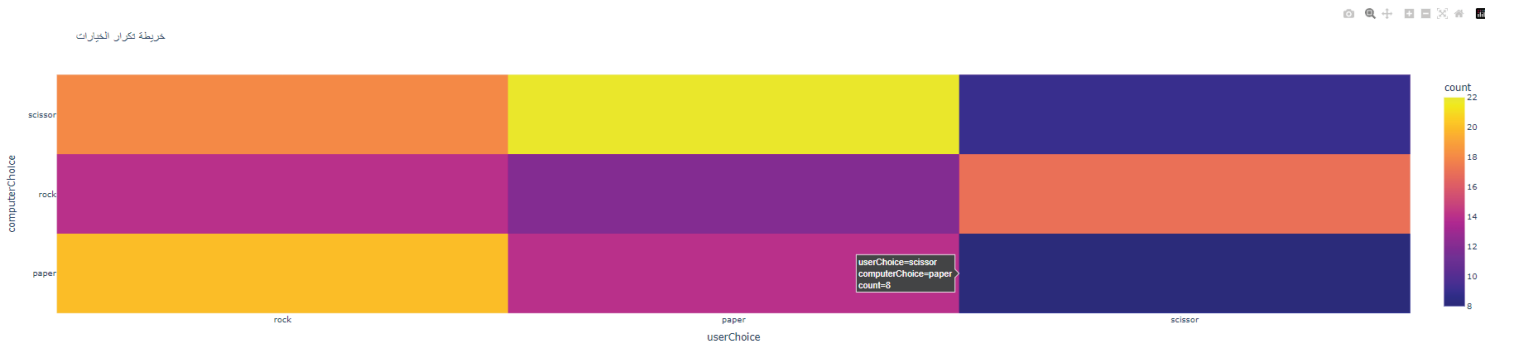

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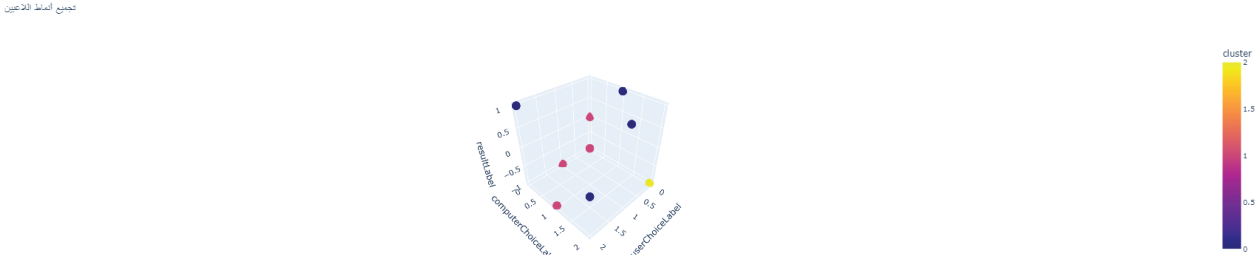

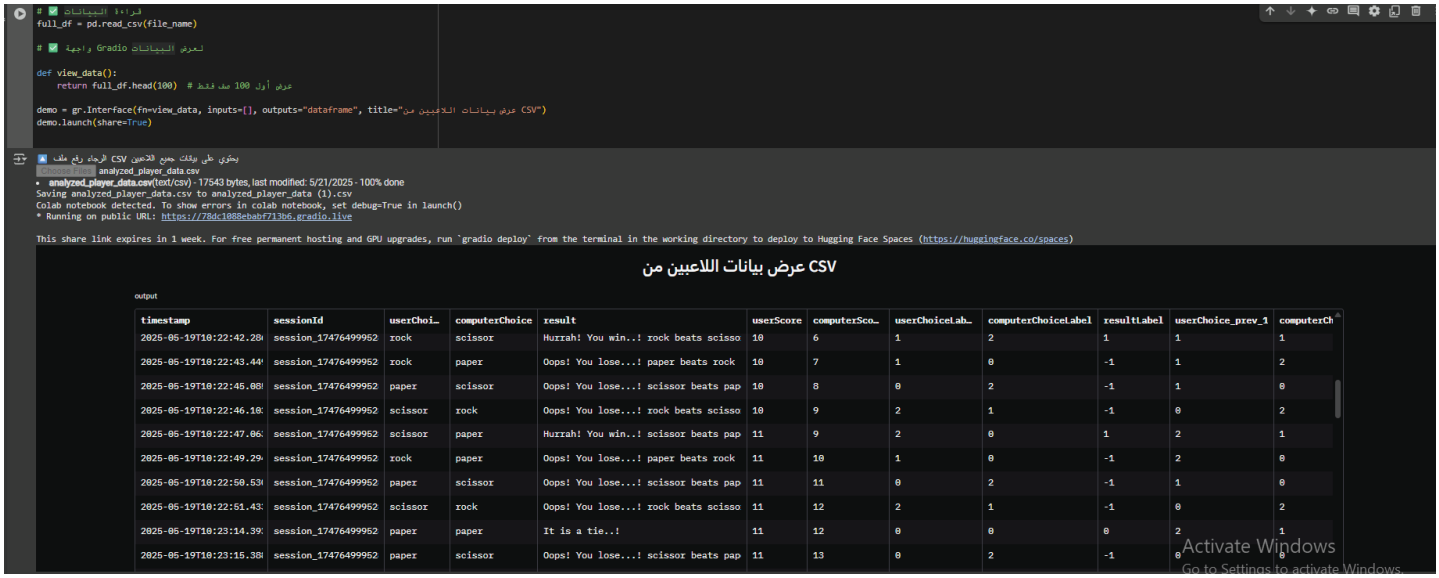

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