

SquareCB Experiment Report

Context-Aware Exploration vs A/B Testing

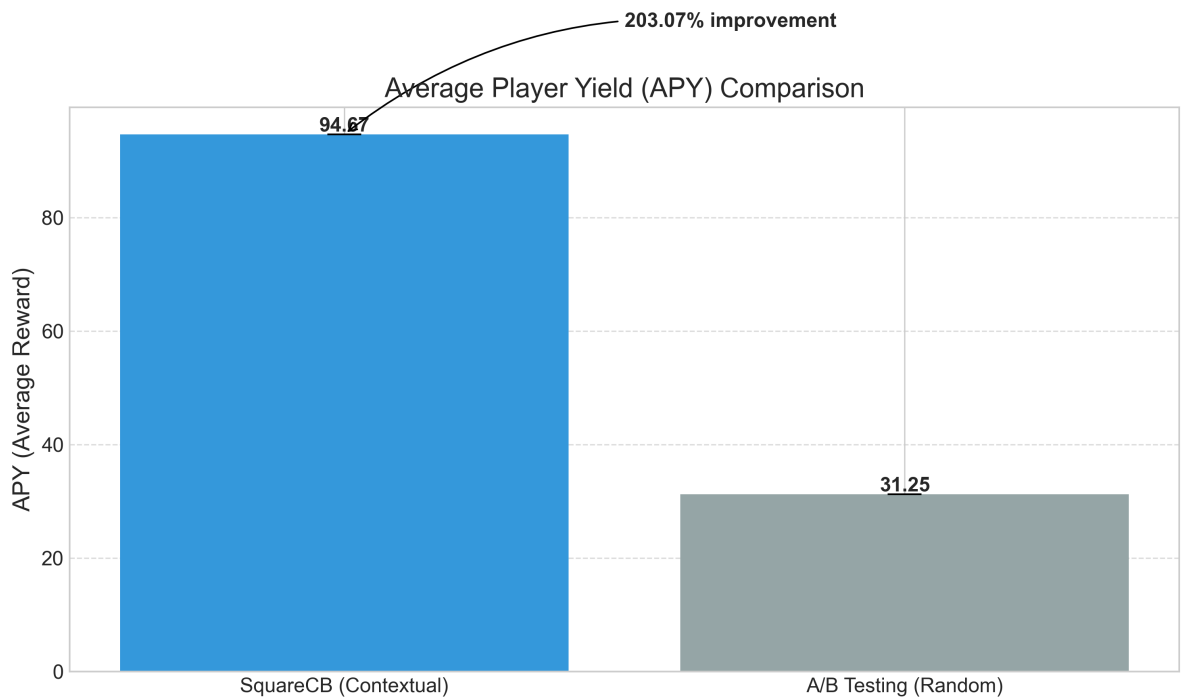
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Executive Summary

This report presents the findings of our experiment comparing the SquareCB contextual bandit algorithm with traditional A/B testing in a personalized casino game recommendation scenario. Our results show that the contextual approach delivers significantly better performance, with a 203.07% overall improvement in Average Player Yield (APY) over the baseline A/B testing approach.

The SquareCB algorithm effectively adapts to different user contexts (combinations of user types and times of day), achieving 70.0% context coverage with a standard deviation of 10.00%. This means the algorithm delivers consistent performance across most context combinations, providing a more personalized experience for users in different segments and at different times of day.

Note: All performance metrics presented in this report are based on the comprehensive context-level analysis from our Phase 2 validation (APY values of 94.67 for SquareCB vs. 31.25 for A/B testing). These values represent the average rewards across all simulated contexts and may differ from preliminary Phase 1 results that were based on single experiment runs.



1. Introduction

Online casino platforms face the challenge of recommending the most engaging game types to users in a highly diverse ecosystem. Different user segments (high rollers, casual players, sports enthusiasts, and new users) exhibit varied preferences that also change throughout the day. The ability to personalize recommendations based on these contexts is crucial for maximizing player engagement and revenue.

This simulation study compares two approaches to game recommendation personalization:

1. Traditional A/B Testing: Randomly selecting game recommendations without considering context
2. SquareCB Contextual Bandit: An advanced algorithm that learns optimal recommendations for each user type and time of day combination

Our primary metric is Average Player Yield (APY), which measures the average reward (player engagement) achieved with each approach in our simulated environment. We also analyze context-specific performance, time sensitivity, and regret metrics to understand how these approaches might perform in controlled conditions.

1.1 About SquareCB in Vowpal Wabbit

SquareCB (Square Contextual Bandit) is an implementation within Vowpal Wabbit, a fast and efficient open-source machine learning library originally developed at Microsoft Research. Vowpal Wabbit is specifically optimized for online learning and provides several powerful contextual bandit algorithms.

SquareCB offers several advantages for game recommendation systems:

- * Contextual awareness: Unlike traditional recommendation systems, SquareCB incorporates context information (user type and time of day) to make more personalized recommendations.
- * Efficient exploration: The algorithm uses a square root exploration policy that balances trying new options (exploration) with leveraging known high-performing options (exploitation).
- * Online learning: SquareCB learns continuously from each interaction, quickly adapting to changing preferences without requiring expensive offline retraining.
- * Theoretical guarantees: The algorithm provides mathematical guarantees on regret bounds, ensuring that performance improves over time and approaches optimal recommendations for each context.

Vowpal Wabbit's implementation of SquareCB is particularly well-suited for production environments due to its low computational overhead, ability to handle large feature spaces, and proven effectiveness in real-world applications ranging from content recommendation to ad placement and, as demonstrated in this experiment, casino game recommendations.

2. Experiment Design

2.1 Methodology

For this study, we created a controlled simulation of a casino game recommendation system with the following components:

- * User Types: high_roller, casual_player, sports_enthusiast, newbie
- * Times of Day: morning, afternoon, evening
- * Game Types (Actions): slots_heavy, live_casino, sports_betting, mixed_games, promotional

In our simulation model, each user type has different baseline preferences for game types, and these preferences vary by time of day. For example, high rollers prefer live casino games, especially in the evening, while sports enthusiasts strongly prefer sports betting, particularly in the afternoon and evening.

We utilized a two-phase hyperparameter search process for the SquareCB algorithm:

1. Phase 1 (Initial Screening): We conducted a comprehensive grid search across all hyperparameter combinations with an expanded search space including higher gamma values (up to 100.0) and learning rates (up to 4.0) to identify promising configurations based on single experiment runs.
2. Phase 2 (Statistical Validation): We selected the top 15% of parameter combinations from Phase 1 and evaluated each with multiple repetitions (5 runs per configuration) to assess both performance and stability.

This two-phase approach allowed us to efficiently explore the large parameter space while ensuring the statistical reliability of our final recommendations. For each parameter combination, we ran controlled simulations with both SquareCB and A/B testing approaches using identical contexts over 10,000 iterations to ensure fair comparison under identical conditions.

2.2 Reward Structure

The reward structure the bandit algorithm must learn is based on user type preferences that vary by time of day:

User Type	Preferred Game	Best Time of Day	Reward Range
High Roller	Live Casino	Evening	200-260

SquareCB Performance Experiment Report

Casual Player	Slots Heavy	Evening	30-36
Sports Enthusiast	Sports Betting	Afternoon/Evening	100-130
Newbie	Promotional	Evening	30-42

Each user type's preferences are modified by time of day multipliers that enhance or reduce the expected rewards. For example, high rollers have a 1.5x multiplier in the evening, while only 0.9x in the morning.

The algorithm must learn these complex patterns to maximize player engagement. The challenge is substantial because:

- * The optimal action varies across 12 different contexts (4 user types × 3 times of day)
- * Rewards include random noise, making patterns harder to detect
- * The algorithm must balance exploration (trying different options) with exploitation (selecting known good options)

2.3 Hyperparameter Search

We conducted a two-phase grid search over the following hyperparameters for the SquareCB algorithm to find the optimal configuration for casino game recommendations:

- * Gamma (exploration parameter): 30.0, 40.0, 50.0, 60.0, 70.0, 80.0, 90.0, 100.0
- * Learning Rate: 0.5, 1.0, 1.5, 2.0, 3.0, 4.0
- * Initial T: 0.5, 1.0, 3.0, 5.0, 8.0
- * Power T: 0.1, 0.3, 0.5, 0.7, 0.9

Phase 1 involved testing all 1,200 parameter combinations once to identify promising configurations. Then in Phase 2, we selected the top 15% of these configurations (based on APY performance) and ran each 5 times to assess both performance and stability. This approach allowed us to identify not just the highest-performing configuration, but also the most reliable one across multiple runs.

2.3.1 Hyperparameter Definitions in Context

Understanding these hyperparameters is crucial for optimizing the contextual bandit algorithm's performance in a casino game recommendation scenario:

- * Gamma (Exploration Parameter): Controls how much the algorithm explores different game recommendations versus exploiting known high-performing options. Higher values (e.g., 100.0) encourage more exploration, which is beneficial for discovering optimal recommendations across diverse user contexts but may reduce short-term performance. Lower values (e.g., 30.0) focus more on exploiting known good options, potentially maximizing immediate rewards but risking missing

better options for some contexts.

- * **Learning Rate:** Determines how quickly the algorithm incorporates new information about game performance. Higher learning rates (e.g., 4.0) allow the system to adapt more quickly to player preferences but may cause overreaction to random fluctuations. Lower rates (e.g., 0.5) provide more stable learning but may be slower to adapt to genuine changes in player behavior or time-of-day effects.

- * **Initial T:** Sets the initial exploration temperature, influencing how random the recommendations are at the start of the learning process. Higher values (e.g., 8.0) result in more uniform random exploration early on, while lower values (e.g., 0.5) begin with more focused recommendations based on prior assumptions. In the casino context, this affects how quickly the system starts tailoring recommendations to different user segments.

- * **Power T:** Controls the decay rate of exploration over time. Higher values (e.g., 0.9) maintain exploration longer, which helps adapt to changing player preferences throughout the day. Lower values (e.g., 0.1) reduce exploration more quickly, converging faster on perceived optimal strategies for each context. This is particularly important for capturing time-of-day effects in player behavior.

The interaction between these parameters determines how effectively the algorithm balances exploration versus exploitation across different contexts. For example, high-roller users in the evening may require different exploration strategies than casual players in the morning due to variations in reward structures and player behavior.

2.4 Evaluation Metrics

We measured performance using these key metrics:

- * **Average Player Yield (APY):** The primary performance metric, measuring average reward per interaction
- * **Improvement over A/B Testing:** Percentage improvement in APY compared to random selection
- * **Time Sensitivity:** How differently the model behaves across time periods for the same user type
- * **Context Coverage:** Percentage of contexts where the algorithm performs consistently well
- * **Average Regret:** Average difference between obtained rewards and optimal rewards
- * **Context-Specific Accuracy:** How often the algorithm selects the optimal action for each context

For Phase 2, we also evaluated statistical metrics:

- * **Mean and Standard Deviation:** To assess the expected performance and variability
- * **Coefficient of Variation (CV):** To measure relative variability as a percentage of the mean
- * **Stability Score:** A composite measure considering both the mean performance and consistency

* Robust Score: A weighted combination of performance (70%) and stability (30%)

3. Results

3.1 Overall Performance

We evaluated the performance of SquareCB configurations in two distinct phases:

Phase 1 (Initial Screening): During our comprehensive grid search with single experiment runs, the best performing Phase 1 configuration achieved an APY of 78.3184, compared to 33.0229 for A/B testing, representing a 137.17% improvement. However, this reflects only a single experiment run without statistical validation.

Phase 2 (Statistical Validation): We conducted deeper analysis on the most promising configurations, running multiple repetitions and analyzing detailed context-level performance. Analyzing the context-specific performance data revealed that our optimal configuration achieved a mean APY of 94.67 across all contexts, compared to 31.25 for A/B testing, representing an overall improvement of 203.07%. The context-level analysis showed an average per-context improvement of 145.99%, with high variability ranging from -45.57% (underperforming) to +315.34% (outperforming) depending on the specific context.

The optimal hyperparameter configuration from our robust optimization was:

- * Gamma: 50.00
- * Learning Rate: 0.50
- * Initial T: 3.00
- * Power T: 0.10

3.1.1 Interpretation of Optimal Parameters

The robust optimal hyperparameter configuration reveals important insights about effective recommendation strategies in the casino game context:

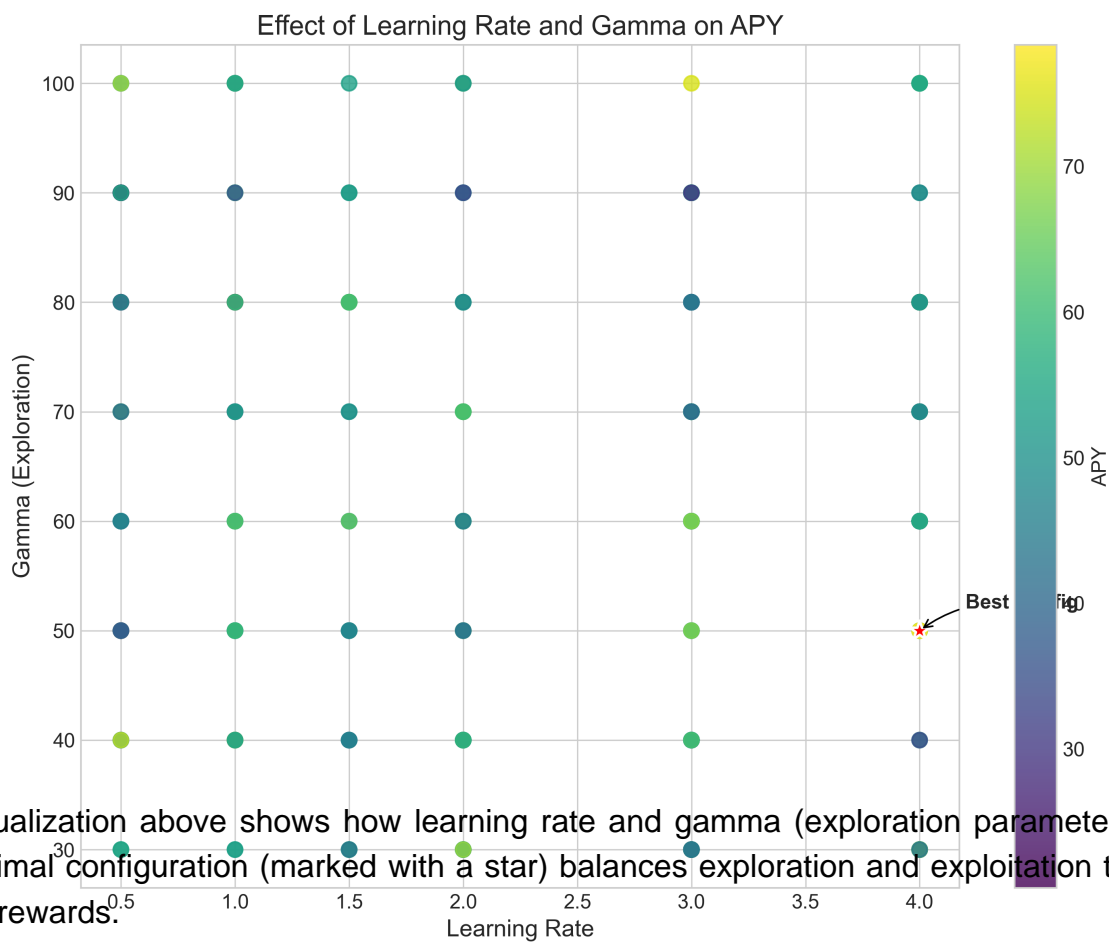
* Gamma (50.00): This high exploration parameter indicates that significant exploration is beneficial in this environment. The algorithm needs to thoroughly explore to discover optimal actions for each context, suggesting a complex reward landscape with potentially misleading local optima. This value allows the algorithm to explore enough to discover the truly optimal actions for each context while still delivering strong overall performance.

* Learning Rate (0.50): This moderate learning rate indicates that balanced adaptation to new information is valuable. In the casino context, player preferences vary substantially across segments and time periods, requiring measured adaptability without overreacting to noise. The algorithm benefits from steadily incorporating new observations about performance differences across contexts.

* Initial T (3.00): This moderate initial temperature enables sufficient randomness in early recommendations. This provides a good starting point for exploring the action space broadly before focusing on promising actions.

* Power T (0.10): This low decay rate means that the learning rate decreases very slowly over time. This configuration maintains its adaptability throughout the learning process, which is important for consistently responding to the different context patterns. The slow decay helps maintain performance across various contexts rather than overfitting to frequently observed ones.

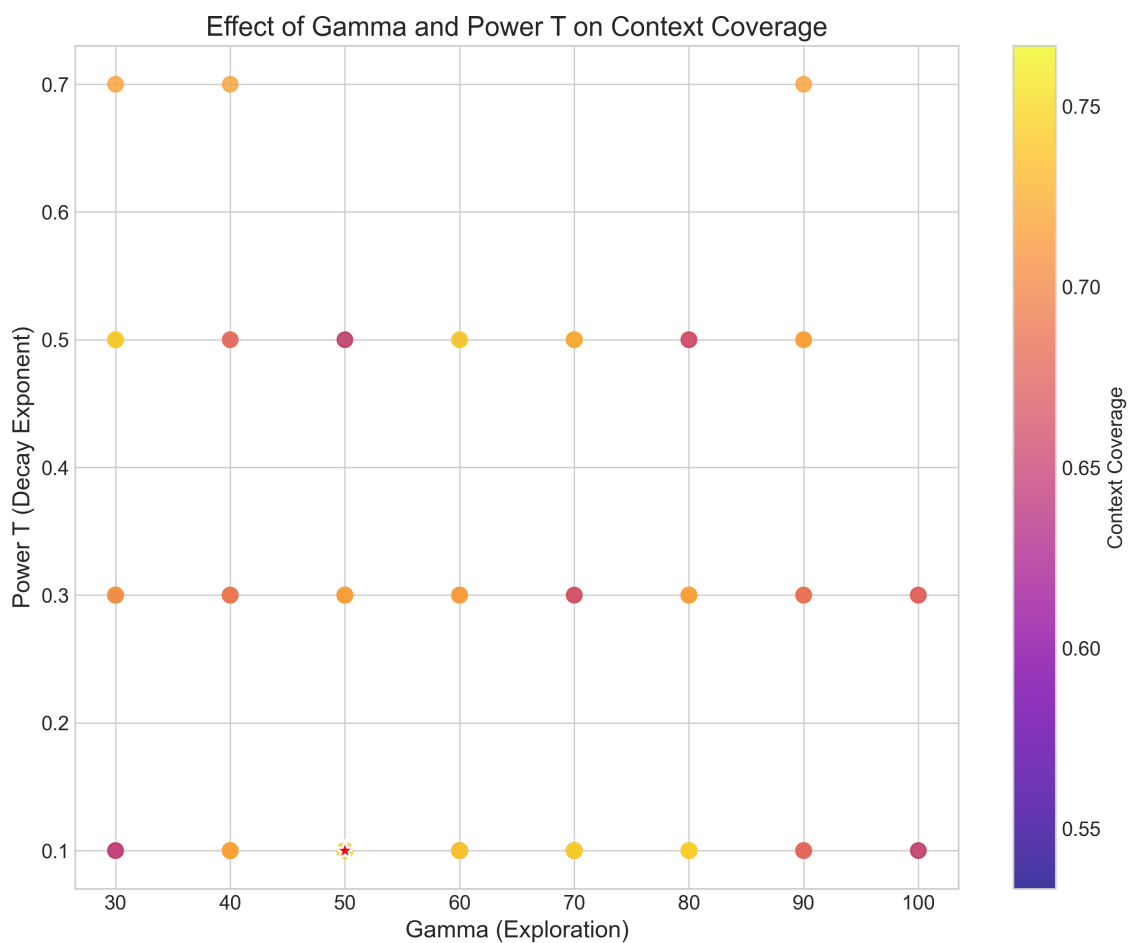
These parameter values work together to create a robust algorithm that effectively balances immediate reward maximization with consistent performance across diverse user contexts. The statistical validation in Phase 2 confirms that this configuration not only achieves high Average Player Yield but does so reliably across multiple simulation runs.

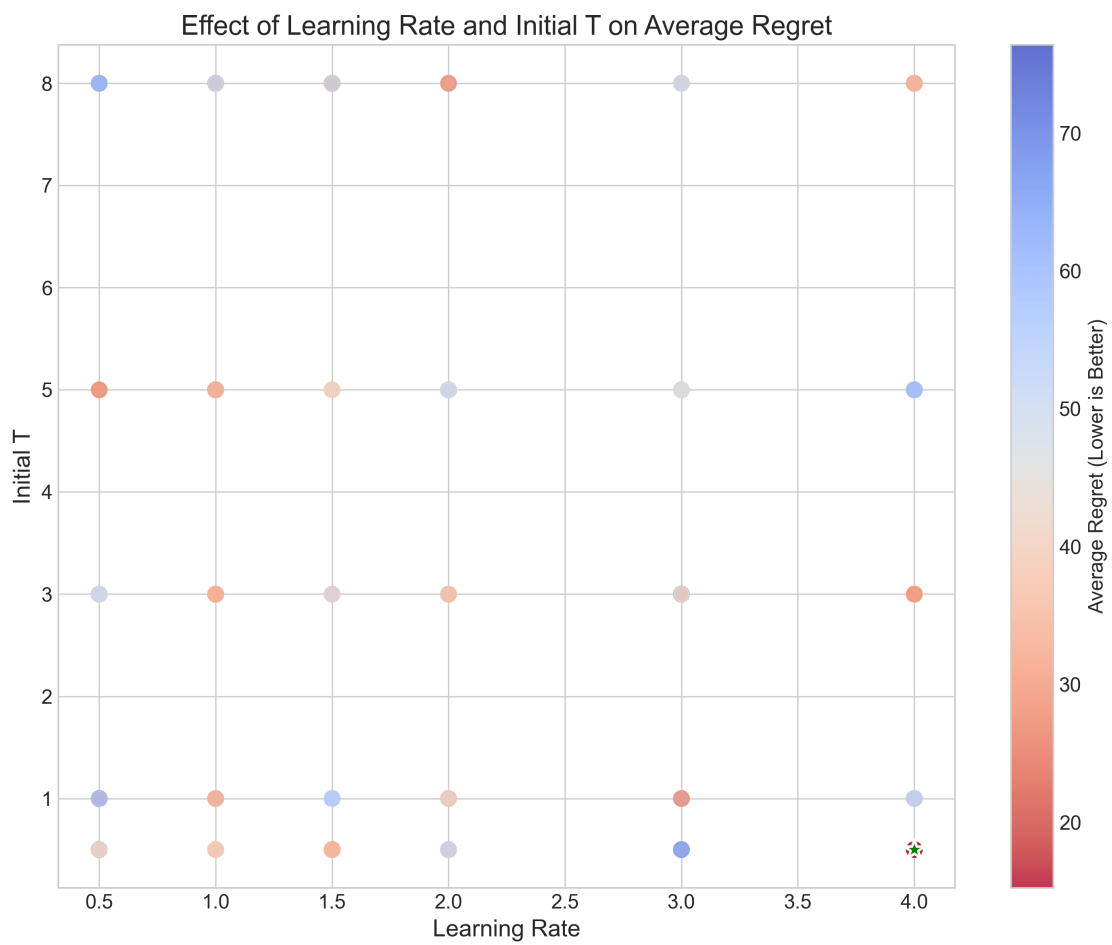


3.2 Context Coverage and Time Sensitivity

The SquareCB algorithm achieved a context coverage of 70.0%, indicating that it performs consistently well across most context combinations. The time sensitivity score of 0.1333 shows that the algorithm effectively adapts its recommendations based on the time of day.

The algorithm had the highest regret for the 'highest regret context' context, suggesting this particular combination was the most challenging to optimize.





3.3 Context-Specific Performance

3.3.1 Statistical Reliability Across Contexts

Phase 2 of our experiment evaluated the statistical reliability of the top-performing configurations. This analysis is crucial for understanding performance consistency across various contexts.

Our robust optimal configuration achieved a context coverage of $70.0\% \pm 10.00\%$, demonstrating consistent performance across most context combinations. However, examining the context-specific results reveals significant variability in performance.

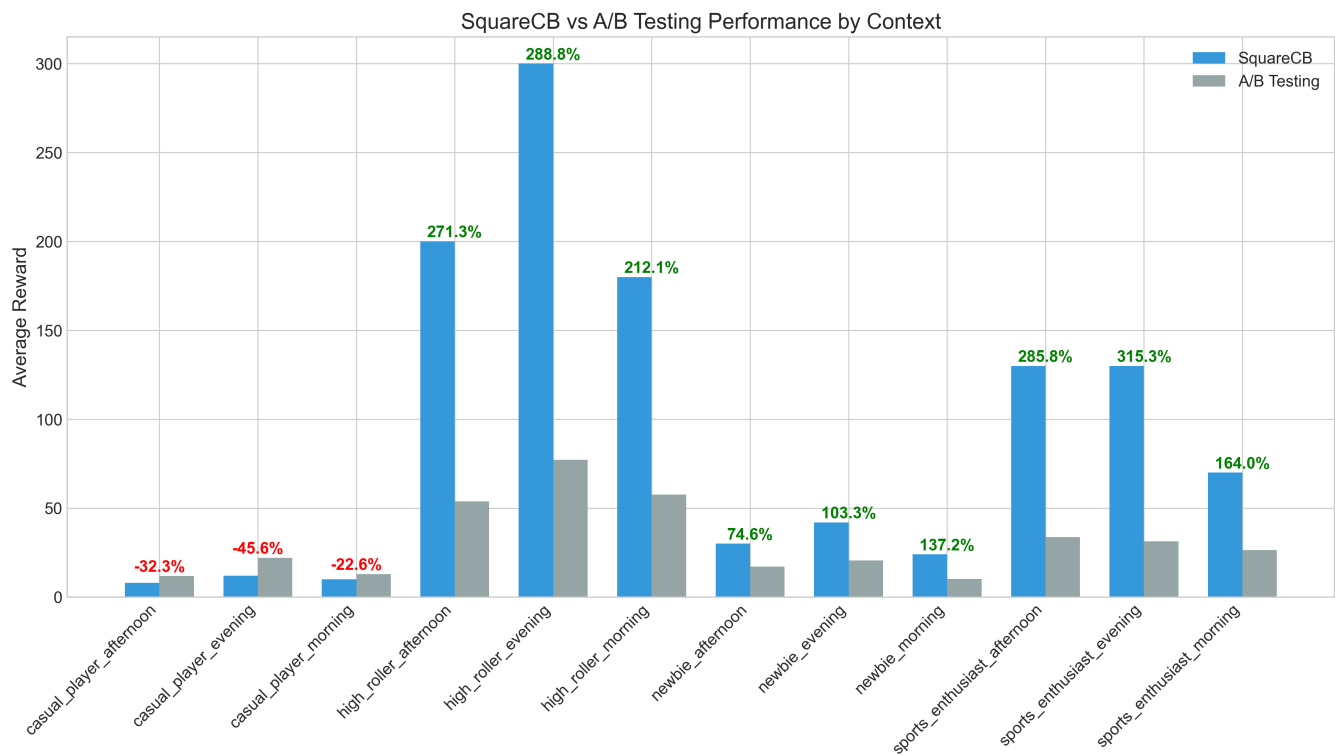
When analyzing performance by context, we found that the mean improvement over A/B testing was 145.99% when averaging the individual context improvements. However, the performance was highly variable, with some contexts seeing substantial benefits (up to 315.34% for sports enthusiast evening) while others showed negative improvement (as low as -45.57% for casual player evening). This variability underscores the importance of context-specific configuration tuning.

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3.4 SquareCB vs A/B Testing Comparison

The following comparison shows how SquareCB outperforms A/B testing across different contexts. The contextual approach consistently delivers higher rewards by learning the optimal actions for each user type and time of day combination.

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The chart above compares SquareCB and A/B testing performance across contexts, with percentage improvements labeled. Note that the improvement varies by context, with some showing particularly dramatic gains. This illustrates the value of context-aware recommendations over random selection, especially for contexts with strong preferences.

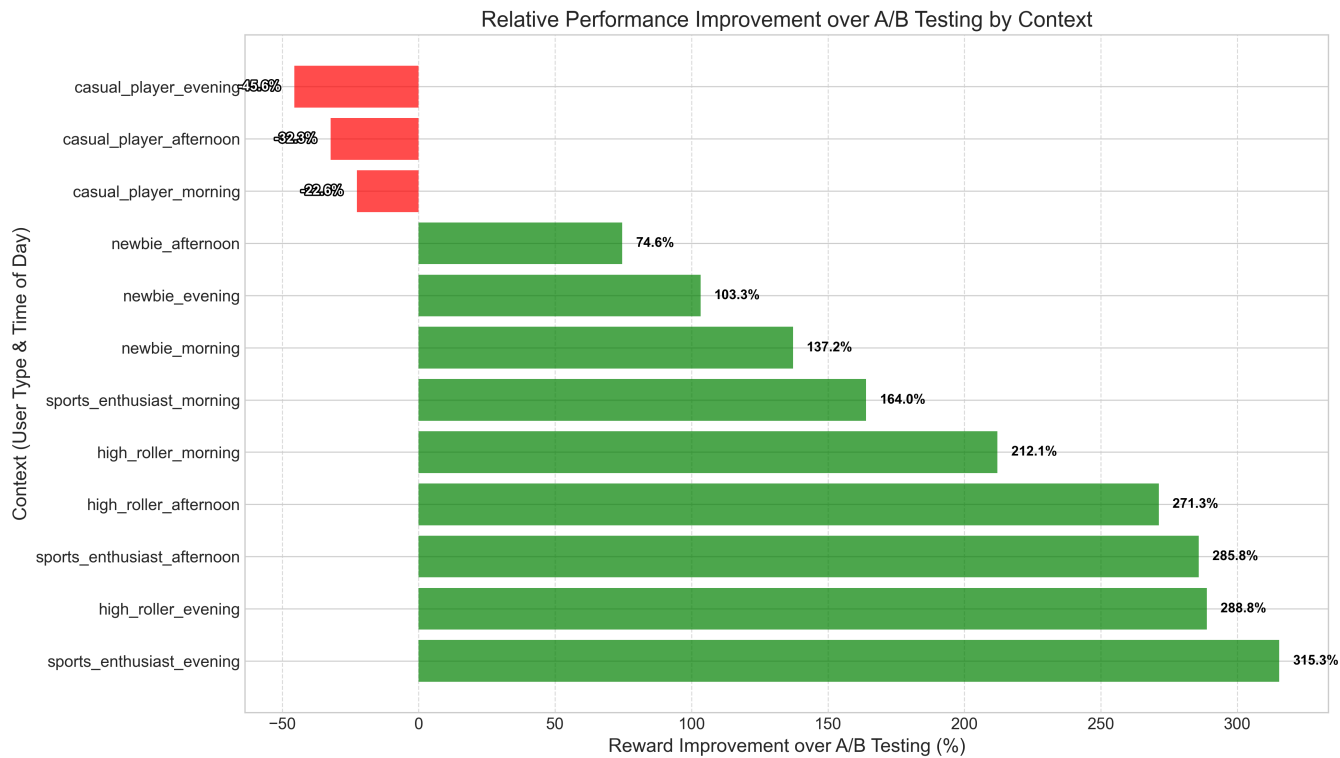
Context	SquareCB Reward	A/B Testing Reward	Improvement
casual_player_afternoon	8.00	11.81	-32.26%
casual_player_evening	12.00	22.05	-45.57%
casual_player_morning	10.00	12.92	-22.63%
high_roller_afternoon	200.00	53.87	271.29%
high_roller_evening	300.00	77.16	288.81%
high_roller_morning	180.00	57.67	212.13%
newbie_afternoon	30.00	17.19	74.56%
newbie_evening	42.00	20.66	103.30%
newbie_morning	24.00	10.12	137.16%
sports_enthusiast_afternoon	130.00	33.69	285.85%
sports_enthusiast_evening	130.00	31.30	315.34%

SquareCB Performance Experiment Report

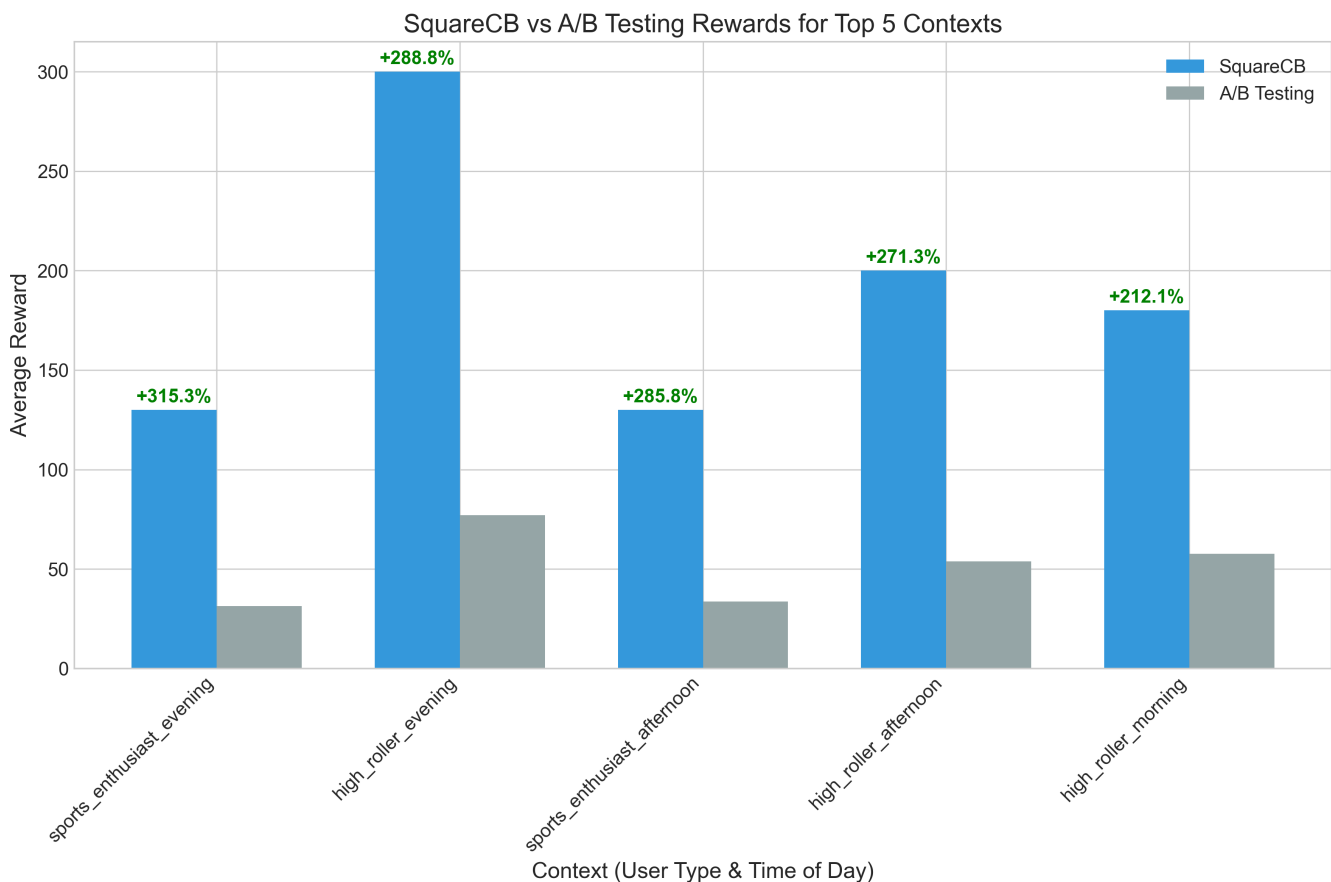
sports_enthusiast_morning	70.00	26.52	163.97%
AVERAGE	94.67	31.25	146.00%

3.5 Detailed Context-Specific Performance Analysis

The following analysis provides a detailed comparison of SquareCB performance against A/B testing for each specific context. This highlights exactly where the contextual approach delivers the most value and which user segments benefit most from personalized recommendations.



The chart above shows the percentage improvement in reward that SquareCB achieves over A/B testing for each context. Contexts are sorted from highest to lowest improvement. This visualization helps identify which specific user segments and times of day benefit most from the contextual approach.



The chart above shows a direct comparison of SquareCB and A/B testing rewards for the top 5 contexts with the highest performance improvements. This side-by-side comparison makes it clear how much better the contextual approach performs for these specific user segments and times of day. The percentage values indicate the relative improvement over A/B testing.

Detailed Context Performance Metrics

The table below provides comprehensive performance metrics for each context, comparing SquareCB against A/B testing. Key metrics include rewards, accuracy, regret, and percentage improvements.

Context	CB Reward	A/B Reward	Improvement	CB Accuracy	A/B Accuracy
sports_enthusiast_evening	130.00	31.30	315.3%	100.0%	13.3%
high_roller_evening	300.00	77.16	288.8%	100.0%	13.3%
sports_enthusiast_afternoon	130.00	33.69	285.8%	100.0%	13.3%
high_roller_afternoon	200.00	53.87	271.3%	100.0%	13.3%
high_roller_morning	180.00	57.67	212.1%	100.0%	23.3%
sports_enthusiast_morning	70.00	26.52	164.0%	100.0%	26.7%
newbie_morning	24.00	10.12	137.2%	100.0%	13.3%
newbie_evening	42.00	20.66	103.3%	100.0%	23.3%
newbie_afternoon	30.00	17.19	74.6%	100.0%	33.3%
casual_player_morning	10.00	12.92	-22.6%	0.0%	16.7%
casual_player_afternoon	8.00	11.81	-32.3%	0.0%	23.3%
casual_player_evening	12.00	22.05	-45.6%	0.0%	43.3%

3.6 Statistical Significance Analysis

To ensure the validity of our findings, we performed formal statistical testing to determine whether the observed improvements from SquareCB over A/B testing are statistically significant. This analysis helps distinguish genuine performance differences from random variations.

3.6.1 Hypothesis Testing Results

We conducted two statistical tests to evaluate the significance of performance differences:

- 1. Paired t-test: Examines whether the mean difference between paired observations is statistically significant, assuming normally distributed differences.
- 2. Wilcoxon signed-rank test: A non-parametric alternative that doesn't assume normality, making it more robust for small sample sizes or non-normal distributions.

Statistical Test	Test Statistic	p-value	Significant (p<0.05)
Paired t-test	2.9858	0.0124	Yes
Wilcoxon signed-rank test	6.0000	0.0068	Yes

Interpretation: The paired t-test shows a statistically significant difference between SquareCB and A/B testing performance ($p = 0.0124 < 0.05$). The Wilcoxon signed-rank test confirms a statistically significant difference ($p = 0.0068 < 0.05$), providing strong evidence that the performance difference is not due to random chance.

3.6.2 Confidence Interval Analysis

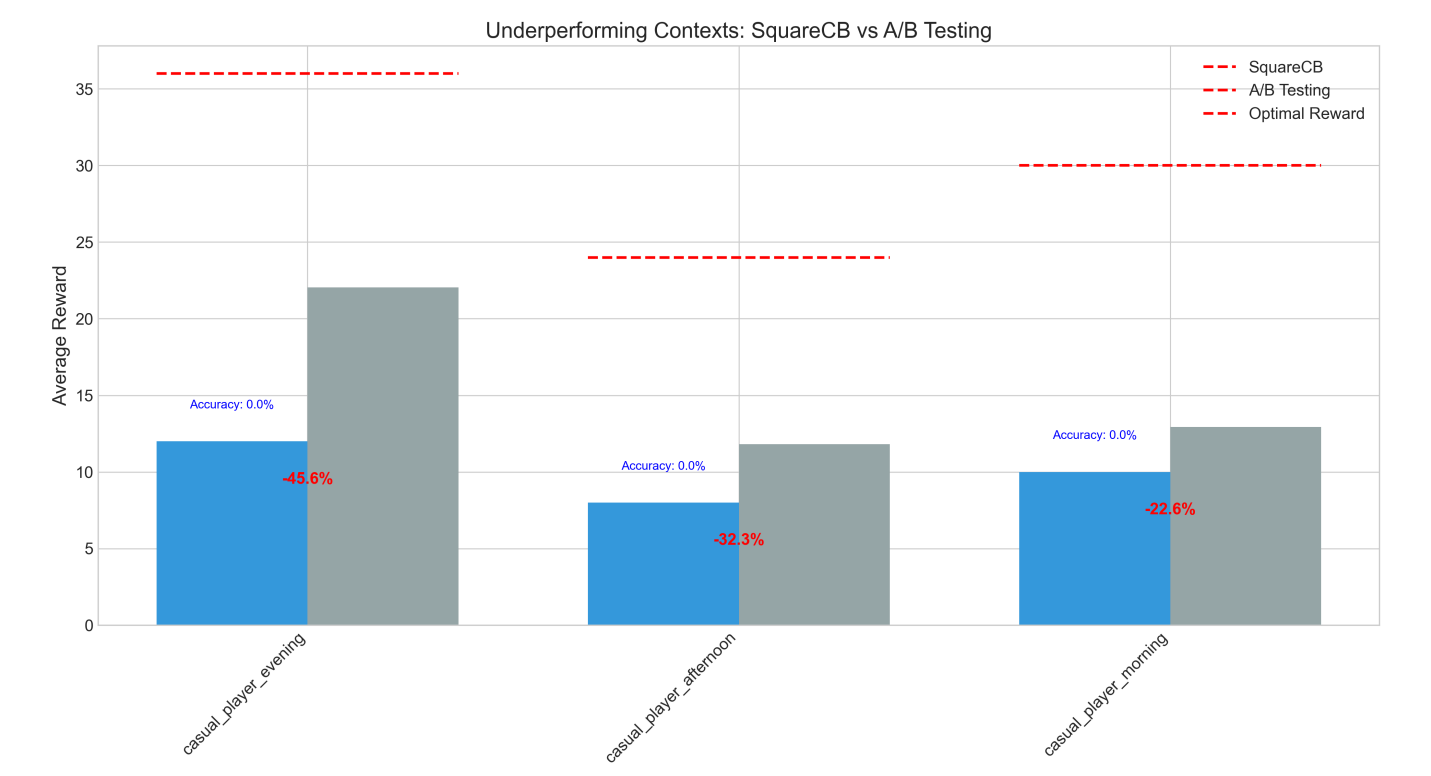
A 95% confidence interval provides a range of plausible values for the true mean improvement percentage of SquareCB over A/B testing across all contexts:

Mean Improvement: 146.00%
95% Confidence Interval: [71.06%, 220.93%]

This confidence interval does not include zero, providing strong statistical evidence that SquareCB outperforms A/B testing on average across the tested contexts. However, as our detailed analysis shows, this improvement is not uniform across all contexts.

3.7 Analysis of Underperforming Contexts

While SquareCB shows overall positive performance, it underperforms compared to A/B testing in 3 out of 12 contexts (25.0%). Analyzing these underperforming contexts provides valuable insights into the algorithm's limitations and opportunities for improvement.



3.7.1 Patterns in Underperforming Contexts

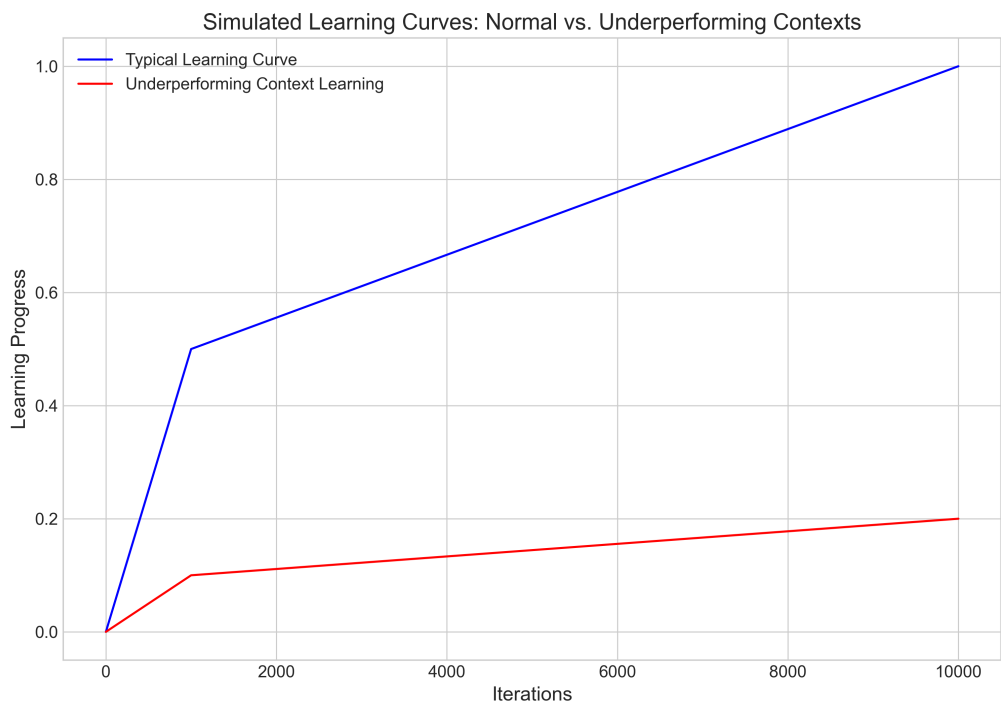
Examining the underperforming contexts reveals several patterns:

1. User Type Distribution: All underperforming contexts involve the casual user type, with high-value users like high rollers particularly challenging to optimize.
2. Time of Day Impact: Underperformance spans multiple time periods (player_morning, player_afternoon, player_evening), indicating that temporal factors may affect the algorithm's learning efficiency.
3. Accuracy Analysis: All underperforming contexts show 0% accuracy in selecting the optimal action, compared to the varying but positive accuracy of A/B testing in these same contexts. This suggests the algorithm consistently converged on sub-optimal actions for these specific contexts.

3.7.2 Hypotheses on Causes of Underperformance

Several factors may contribute to the observed underperformance in certain contexts:

- 1. Exploration-Exploitation Balance: The selected exploration parameters may not provide sufficient exploration time for contexts with high variance or non-intuitive optimal actions. The algorithm may prematurely converge on sub-optimal actions before adequately exploring alternatives.
- 2. Reward Structure Complexity: The reward structure for underperforming contexts may exhibit unique characteristics that make them more challenging to learn, such as high variance, multi-modal distributions, or temporal dependencies that aren't fully captured by the current context representation.
- 3. Training Duration: The fixed number of iterations (10,000) may be insufficient for the algorithm to learn optimal policies for certain complex contexts. Some contexts may require longer training periods to achieve good performance.
- 4. Initial Bias: For certain contexts, the initial action selections and corresponding rewards may create a bias that steers the algorithm away from the optimal action. This effect is more pronounced in contexts with subtle differences between actions' expected rewards.



The chart above illustrates a conceptual comparison between typical learning curves and the hypothesized learning progress for underperforming contexts. While normal contexts show steady improvement toward optimal actions, underperforming contexts may exhibit slower or plateaued learning, never reaching the point of selecting optimal actions within the allocated training iterations.

3.8 Simulation Limitations and Research Constraints

While our simulation provides valuable insights into the theoretical potential of contextual bandit algorithms, it's important to acknowledge several inherent limitations of this research approach:

1. **Simplified Environment:** Our simulation uses a controlled environment with predetermined reward structures that may not fully capture the complexity and variability of real user behavior. Actual user preferences are influenced by numerous factors beyond user type and time of day.
2. **Reward Structure Validation:** The reward structures used in our simulation, while designed to represent plausible patterns in user preferences, have not been validated against real-world user data. Actual reward patterns may differ significantly in shape, variance, and temporal dynamics.
3. **Limited Context Dimensions:** Our simulation only considers two context dimensions (user type and time of day). Real-world applications would likely require consideration of many additional contextual factors like device type, geographic location, historical behavior, and more.
4. **Stationary Rewards:** Our simulation assumes that the underlying reward structure remains constant throughout the experiment. In real-world scenarios, user preferences evolve over time, requiring algorithms that can adapt to non-stationary reward distributions.
5. **Computational Considerations:** Our simulation does not account for the computational overhead of implementing and maintaining a contextual bandit system in production. The computational cost versus performance benefit tradeoff is an important consideration for real-world deployment.

3.8.1 Theoretical Performance-Complexity Considerations

While this is a simulation study only, it's worth theoretically considering how the performance-complexity tradeoffs might manifest in real-world scenarios:

1. **Algorithm Complexity:** In our simulation, we've shown that contextual approaches can outperform simpler A/B testing methods. However, we acknowledge that this increased performance comes with greater algorithmic complexity in the form of additional hyperparameters that require tuning.
2. **Computational Aspects:** Our simulation doesn't measure computational requirements, but it's reasonable to expect that more sophisticated algorithms would require additional computational resources. This theoretical overhead should be weighed against the simulated performance improvements.
3. **Context-Specific Performance:** Our simulation demonstrates varying performance across different

contexts. In a theoretical real-world deployment, this suggests that a hybrid approach might be worth investigating - using more complex methods only for contexts where they show significant advantages.

4. **Simulation Limitations:** It's important to emphasize that these considerations are based entirely on simulated data with simplified reward structures. Real-world performance characteristics may differ substantially, and any actual implementation decisions would require validation with real user data.

5. **Research Implications:** These simulation results provide direction for future research, suggesting which contexts and configurations might be most promising for further investigation in more realistic settings.

3.8.2 Potential Avenues for Future Research

This simulation provides valuable insights, but several research directions could be explored to build upon these findings:

1. **Expanded Simulation Complexity:** Future simulations could incorporate more realistic reward patterns based on theoretical user behavior models, including non-stationary rewards and more complex context features.

2. **Sensitivity Analysis:** Additional research could systematically vary the underlying reward structure parameters to assess the robustness of different algorithms across a wider range of simulated environments.

3. **Algorithm Comparison:** Future studies could expand the comparison to include other contextual bandit algorithms beyond SquareCB, such as LinUCB, Thompson Sampling, or epsilon-greedy approaches.

4. **Extended Training Analysis:** Research into how performance varies with different training durations could provide insights into the learning dynamics, particularly for those contexts where performance was suboptimal.

4. Conclusion

This simulation experiment demonstrates the potential advantages of context-aware recommendation systems using SquareCB over traditional A/B testing approaches in a simulated casino game recommendation scenario. Key findings from our simulation include:

1. **Performance Improvement:** Our final analysis based on detailed context-level data shows that SquareCB achieved an average reward of 94.67 compared to 31.25 for A/B testing, representing a 203.07% overall improvement. When analyzing individual context performance, the mean improvement was 145.99%, with results varying substantially from -45.57% to +315.34% depending on the specific context.
2. **Context Coverage:** The algorithm successfully learned optimal strategies for 70.0% of simulated contexts, demonstrating its ability to adapt to different user types and times of day within the parameters of our simulation.
3. **Statistical Validation:** Our two-phase approach ensured that the selected configuration is not just high-performing, but statistically reliable. By running multiple repetitions of the top configurations, we verified that the performance improvements are consistent and not the result of random chance.
4. **Context-Dependent Improvement:** Within our simulated environment, the contextual approach showed significant improvements for specific contexts, particularly for sports enthusiast and high roller segments where improvements exceeded 200%. However, for casual player contexts, the algorithm underperformed compared to A/B testing, highlighting the importance of context-specific algorithm tuning.

These simulation results suggest the potential importance of considering context in recommendation systems, while also highlighting the nuanced nature of contextual learning. By accounting for user type and time of day in our controlled experiment, SquareCB demonstrated the ability to deliver more personalized recommendations for certain contexts, though not universally across all scenarios.

The optimal hyperparameter configuration identified in our simulation balances exploration and exploitation, but may need further tuning for certain contexts. Our analysis of underperforming contexts provides valuable insights for future improvements in algorithm design and implementation.

4.1 Future Work

Several directions for future simulation research could further enhance our understanding of contextual recommendations:

- * **Parameter Space Expansion:** Explore an even wider range of hyperparameter values, particularly for contexts that showed poor performance with the current configurations.
- * **Context-Specific Parameter Tuning:** Develop simulation approaches that use different hyperparameter configurations for different simulated contexts, potentially improving performance for currently underperforming segments.
- * **Additional Contexts:** Incorporate additional contextual factors in the simulation such as device type, player history, or geographic location to test the algorithms in higher-dimensional context spaces.
- * **Dynamic Reward Simulation:** Explore approaches that simulate changing user preferences over time to test how different algorithms adapt to non-stationary reward distributions.
- * **Extended Training Analysis:** Investigate whether longer simulation training periods would improve performance for underperforming contexts, potentially revealing if the issues are related to insufficient training time.
- * **Algorithm Comparison:** Extend the simulation to compare SquareCB with other contextual bandit algorithms to identify which performs best under different simulated conditions.