# **Introduction:**

### The project involves analyzing a gaming behavior dataset consisting of player details and level details.

### Players engage in a game with three levels (L0, L1, and L2), each with three difficulty levels.

### The objective is to extract insights into player performance, progression, and behavior within the game environment.

# **Dataset Description:**

### The dataset comprises two tables: Player Details (pd) and Level Details (ld).

### Player Details table contains player ID, name, status for levels L1 and L2, and corresponding codes.

### Level Details table stores player ID, device ID, start time, stages crossed, level, difficulty, kill count, headshots count, score, and lives earned.

# **Project Objectives:**

### Analyze player behavior, progression, and performance within the game environment.

### Extract insights on kill counts, scores, lives earned, and other gameplay metrics.

### Identify patterns, trends, and correlations in player data across different levels and difficulty levels.

# **Data Analysis:**

### Extracted player ID, device ID, player name, and difficulty level for players at level 0.

### Calculated the average kill count for Level 1 codes where players earned 2 lives and crossed at least 3 stages.

### Determined the total stages crossed at each difficulty level for Level 2 players using 'zm\_series' devices.

### Identified players who played games on multiple days and calculated the total unique dates for each player.

### Analyzed the sum of kill counts for players where kill count exceeded the average kill count for Medium difficulty.

### Summarized the total lives earned for each level and corresponding level codes, excluding level 0.

### Ranked top scores based on each device ID and displayed difficulty levels.

### Found the first login datetime for each device ID.

### Ranked top scores based on each difficulty level and displayed corresponding device IDs.

### Determined the device ID that was first logged in for each player along with the first login datetime.

### Calculated the total kill counts played by each player for each date using window function and without using window function.

### Found the cumulative sum of stages crossed over start datetime for each player, excluding the most recent start datetime.

### Extracted the top 3 highest sums of scores for each device ID and the corresponding player IDs.

### Identified players who scored more than 50% of the average score scored by the sum of scores for each player.

### Created a stored procedure to find the top N headshots count based on each device ID and ranked them in increasing order using Row\_Number.

# **Key Findings:**

### Players at level 0 predominantly play at Low difficulty.

### Players tend to perform better in Level 1 codes where they earn 2 lives and cross at least 3 stages.

### Level 2 players using 'zm\_series' devices cross more stages at difficult level compared to other levels.

### Some players engage in the game on multiple days, indicating sustained interest.

### Certain players excel in Medium difficulty, surpassing the average kill count.

### Players earn varying numbers of lives across different levels and corresponding codes.

### Top scores vary based on device ID and difficulty level.

### Players typically log in with different devices, with varying first login datetimes.

### Top scores differ across difficulty levels, with corresponding device IDs.

### The first login datetime varies for each player and device ID.

### Players' kill counts accumulate over time, with fluctuations across dates.

### Cumulative stages crossed decrease over start datetime for each player, excluding the most recent start datetime.

### Top scores vary for each device ID, indicating varying player performance.

### Players scoring above 50% of the average score demonstrate above-average performance.

### The stored procedure efficiently ranks top N headshots count based on each device ID.

# **Final Outcome:**

### The project successfully extracts valuable insights into player behavior, performance, and progression within the game environment.

### Detailed analysis of gameplay metrics provides actionable insights for game developers to enhance user experience and engagement.

# **The Future Scope:**

### Implement predictive analytics to forecast player behavior and identify potential churn.

### Integrate real-time analytics to monitor player engagement and adjust game dynamics accordingly.

### Explore machine learning algorithms to personalize gameplay experience and recommend tailored challenges.

### Collaborate with game developers to implement feedback loops based on player data for continuous improvement.

### Extend analysis to include player demographics, geographical data, and social interactions for comprehensive understanding.

### Enhance visualization techniques to present insights in an intuitive and interactive manner for stakeholders.

# **Conclusion:**

### The project offers valuable insights into gaming behavior, enabling game developers to optimize gameplay experience and drive user engagement.

### By leveraging data analytics, game developers can make informed decisions to enhance game dynamics, address player preferences, and maximize player retention.

### Continuous monitoring and analysis of player data are essential for staying competitive in the dynamic gaming industry and delivering immersive gaming experiences.