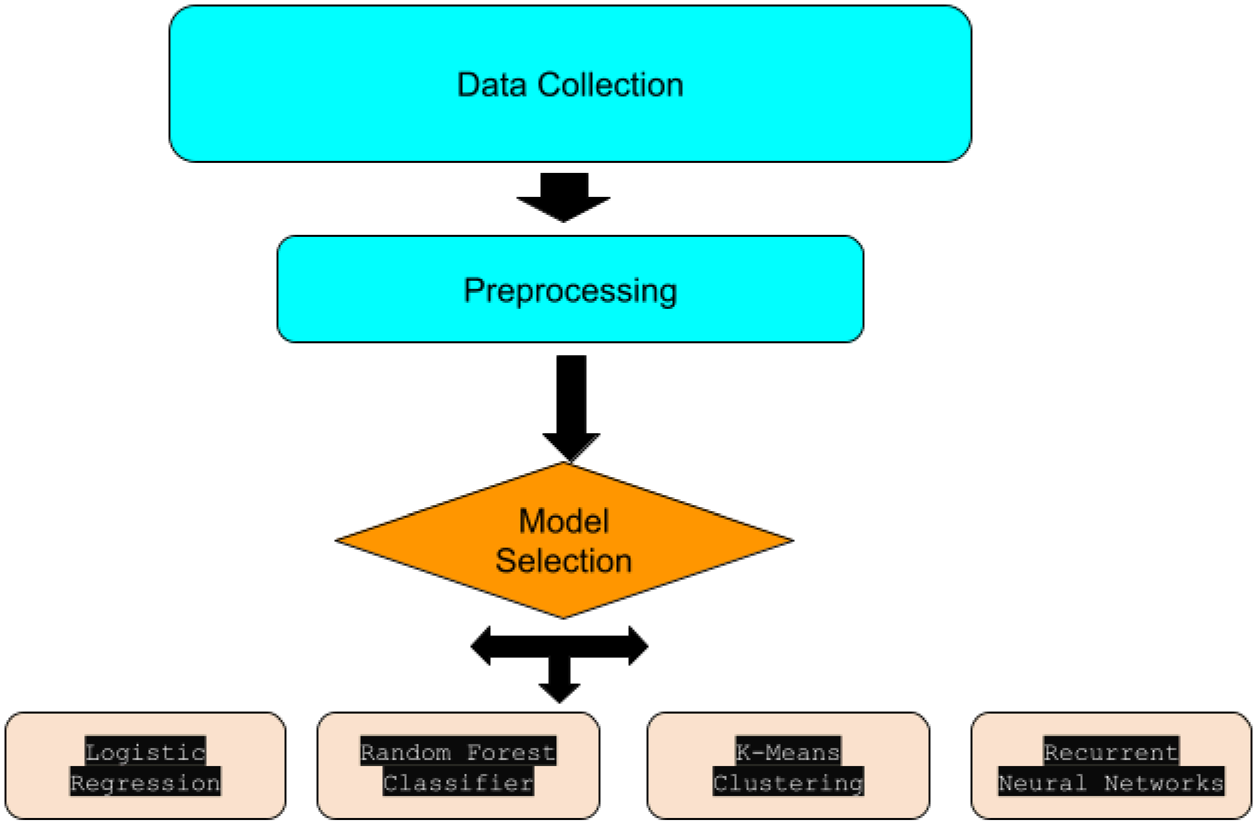

Data Collection: Use a process symbol to represent the step of collecting data from browser activity/events.
Preprocessing: Connect the data collection step to a preprocessing symbol, indicating the cleaning and preparation of the collected data.
Feature Engineering: Connect the preprocessing step to a feature engineering symbol, representing the creation and selection of relevant features from the data.
Model Selection: Connect the feature engineering step to a decision symbol, indicating the branching point for selecting different AI/ML models.
Eg. Logistic Regression, Random forest, K-Means clustering, Recurrent Neural Network.

List of potential data points to collect from the browser activity/events for the 3D Trading Card Game

By collecting these data points, we can gain insights into various aspects of player behavior, engagement, social interaction, monetization, and technical performance within the game. These insights can then be analyzed to understand factors influencing player retention and inform strategies for improving the gaming experience and increasing player retention rates.
[NOTE : Assumptions made by current Progression of the Game]

1. Player Engagement Metrics:
    - Time spent in the game per session
    - Frequency of logins per day/week/month
    - Average session duration
    - Number of matches played per session/day/week
    - Duration of each match
2. Gameplay Metrics:
    - Match outcomes (win/loss/draw)
    - Types of game modes played (e.g., single-player, multiplayer, tournaments)
    - Most frequently chosen characters/cards
    - Level progression of characters/cards
    - Unlocking of new characters/cards or abilities
    - Actions taken during gameplay (e.g., attacks, defenses, trades)
3. Social Interaction Metrics:
    - Participation in multiplayer matches or events
    - Communication and interaction with other players (if available)
    - Formation or participation in player guilds or communities
4. Monetization Metrics (if applicable):
    - In-game purchases (e.g., character upgrades, skins, boosts)
    - Conversion rate from free-to-play to paying players
    - Average revenue per user (ARPU) from in-game transactions
5. Real-time Performance Metrics (blinking parameters):
    - Latency (ms)
    - Memory usage (MB)
    - Frame rate (FPS)

MODELS

Logistic Regression:

Logistic Regression is a widely used statistical technique for binary classification tasks, making it suitable for predicting user churn (retention vs. non-retention) based on various features collected from player engagement, gameplay, social interaction, and monetization metrics. In the context of the 3D Trading Card Game, logistic regression can analyze factors such as session duration, frequency of logins, match outcomes, and in-game purchases to determine their impact on player retention. By estimating the probability of churn for each player, logistic regression helps identify key predictors influencing user retention and provides actionable insights for improving player engagement strategies and reducing churn rates.

Random Forest:

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. It is highly effective for both classification and regression tasks and is particularly useful for analyzing complex interactions and nonlinear relationships in the data. In the context of user retention in the 3D Trading Card Game, Random Forest can leverage features such as player engagement metrics, gameplay behavior, social interactions, and monetization patterns to predict player churn. By constructing an ensemble of decision trees and aggregating their predictions, Random Forest can identify the most influential factors contributing to user retention and provide valuable insights for optimizing game features, enhancing player experiences, and reducing churn rates.

K-Means Clustering:

K-Means Clustering is an unsupervised learning algorithm used for grouping similar data points into clusters based on their characteristics. In the context of user retention analysis, K-Means Clustering can segment players into distinct groups or clusters based on their behavior, engagement patterns, and other relevant metrics collected from the game. By clustering players with similar retention behaviors together, this model helps identify common traits and preferences among different player segments, enabling personalized retention strategies tailored to each cluster. For example, K-Means Clustering can group players based on their frequency of logins, session duration, or in-game purchases, providing insights into the distinct needs and preferences of different player segments and guiding targeted interventions to improve user retention.

Recurrent Neural Network (RNN):

Recurrent Neural Network (RNN) is a type of deep learning model designed to process sequential data by capturing dependencies over time. In the context of user retention analysis for the 3D Trading Card Game, RNNs can analyze sequential player actions, such as in-game interactions, gameplay events, and engagement patterns, to predict future player behavior and retention outcomes. By learning from the temporal dynamics of player interactions, RNNs can uncover complex patterns and relationships in the data, enabling accurate predictions of user retention and churn. Additionally, RNNs can incorporate contextual information from previous game sessions to adaptively adjust retention strategies and interventions, thereby optimizing player experiences and maximizing retention rates over time.