Classification of engagement levels using random forest for gamified environments*

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Abstract

In the current reality of improved live satisfaction, thanks to digitalization and globalization, young population have high availability of entertainment services, especially videogames, hence they tend prefer more gamified environment. Most areas can implement this to increase user engagement. In this study we identified important features, taken from SAGE (Smart Adaptive Gamified Education) dataset, that describes video game statistics of respondents, by using random forest for classifying player engagement levels into low, medium, and high categories based on various engagement metrics. We identified important features and correlations that highlight the key factors for improving engagement. In future studies use of classification and clustering will give a promising result at identifying features that can be used in gamified environments in real time to adjust mechanics (or rules) individually, increasing user engagement, and predicting unwanted results, like failure of students or losing clients. Furthermore, integrating deep learning techniques alongside traditional machine learning methods can enhance predictive accuracy and provide deeper insights into engagement patterns. Exploring user behavioral trends over time and analyzing adaptive learning strategies may also lead to more personalized and effective gamified experiences.

Keywords

gamification, artificial intelligence, random forest, engagement, education

1. Introduction

Gamification is used in many fields, like education, business, marketing. Implementation of this concept can drastically improve performance metrics. With the large number of young gamers across the globe, adoption of AI technologies in gamification is relevant in current reality [1]. High availability of digital entertainment services, especially games, led to the addiction to them by young population.

Besides, oftentimes in game environments they perceive and process information better than in real life, like making math for maximizing values for winning in games, as experienced times by times by some authors of this research.

Gamification in the field of education has become a crucial approach to address challenges in pedagogy. Keeping student engagement was always one of the most difficult tasks for teachers. Traditional methods often struggle with that task due to a lack of motivation from students toward old approaches.

Students' engagement and attendance is very important for academic organizations, and thus it can be improved by AI enhanced gamification [2].

In current digital era, there are different methods that offer interactivity and feedback through games and social platforms. Machine learning approaches can process non-linear and complex data with multiple dimensions. Implementation of AI can improve game mechanics by adjusting algorithms for personalized game efforts [3].

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In this study we will identify features that is important for engagement in gamification by implementing Random Forest classification.

2. Literature review

There are different researches in implementing AI in gamification. In the study, conducted by [4], prediction problem was used as classification problem for early identification of final outcomes of students in the course, in which students are offered to choose between traditional and gamified approaches. In modern approach they identified an important quantitative variable for improvement in the course. Their methodology can be used on small datasets.

Certain study used concept of gamification in assisting students at learning human anatomy, with the help of virtual assistant at giving recommendations for improving needed aspects [5].

Gamification approach with machine learning can be implemented for improving ecology by increasing user involvement in sorting waste in correct garbage [6]. It can also contribute to ecology by motivating people for efficient energy usage in smart infrastructures, with implementation of bi-directional Recurrent Neural Networks for improved forecasting of actions [7].

Gamification can also be used in improving critical thinking abilities in education. The solution as Adaptive Critical Thinking Enhancement System (ACTES) were proposed by Correia et al. [8], in which gamified learning modules, evaluation algorithms, insights monitoring panel, cooperative solution finding platform are provided.

Compared to gamification, adaptive gamification in education can be used for adaptation of the system for the certain type of person, depending on involvement with gamified environment [9].

In some cases, gamification have low impact on improving cognitive load due to lack of support and structured assistance from the teacher or platform, as shown in work on programming education of Zhan et al. [10]. They concluded, that for increasing the motivation of students, puzzle games are the most effective, while for increasing academic achievements, reasoning strategy games are worth implementing. Besides, gamified applications, that were used as teaching tools improved academic achievements, while application used as rivalry- driven mechanisms improved motivation and thinking skills.

3. Research methods

In our study we used SAGE (Smart Adaptive Gamified Education) dataset [11]. This dataset is made by conducting a survey and consists of 1929 items, which is enough for our analysis. It consists of demographic data, preferred game genres, gaming experience, and gamification preferences of respondents.

Time per week is taken as engagement level as low, medium and high for our analysis in order to make predictions about important features in player (any subject of gamification, like education or marketing) engagement.

Analysis is made with the support of sklearn Random Forest Classifier for making engagement classification.

The Random Forest (RF) algorithm is an ensemble learning method that constructs multiple decision trees during training and aggregates their predictions through majority voting (for classification) or averaging (for regression) [12]. The classifier was configured with number of estimators equal to 100, indicating 100 decision trees in the ensemble.

The random state has 42 parameter ensured reproducibility of results. RF was chosen for its ability to:

- Process the mixed data types and non-linear relationships.
- Give interpretability through feature importance scores.
- Avoid overfitting as much as possible in contrast to individual decision trees.

StandardScaler standardizes features by removing the mean and scaling to unit variance [13].

$$z = \frac{x - \mu}{\sigma}, \tag{1}$$

where μ is the mean, σ is the standard deviation.

LabelEncoder converts categorical target labels into numerical values, enabling compatibility with Scikit-Learn’s classification algorithms [14].

Engagement levels were derived from time_per_week using quantile-based discretization (pd.qcut), ensuring balanced class distributions. Data was split into 80% training and 20% testing sets (test_size=0.2), preserving class distribution via stratification. Features included 17 engagement mechanics (e.g., "cooperation," "storytelling"), while the target was the encoded engagement level.

Confusion matrix highlights true vs. predicted class distributions [15].

ROC curve analysis enhances the evaluation of the Random Forest Classifier's performance by providing a threshold-independent perspective on class classification [16, 17].

Feature correlation analysis is very crucial at understanding the relationships between different predictive variables [18, 19]. Highly correlated features may indicate redundancy, while weak correlations can suggest independence, and by visualizing correlations within the top 10 most important features, we can gain insights into how these features interact and their potential impact on the model’s predictions [20, 21].

The correlation matrix quantifies the strength and direction of relationships between the features, ranging from -1 (strong negative correlation) to +1 (strong positive correlation), and in this study Pearson’s correlation coefficient were used [22, 23].

$$r_{X,Y} = \frac{\sum (X_i - X)(Y_i - Y)}{\sqrt{\sum (X_i - X)^2 \sum (Y_i - Y)^2}} \tag{2}$$

In order to visualize and analyze how features, vary across different engagement levels, Kernel Density Estimate (KDE) plot is used.

4. Results and discussion

The model is generally quite effective at predicting the true label when it's "Medium," with the highest number of correct predictions (59). Low engagement is often misclassified as High (44 times), suggesting the model sometimes overestimates engagement levels for low-engagement players (Fig.1).

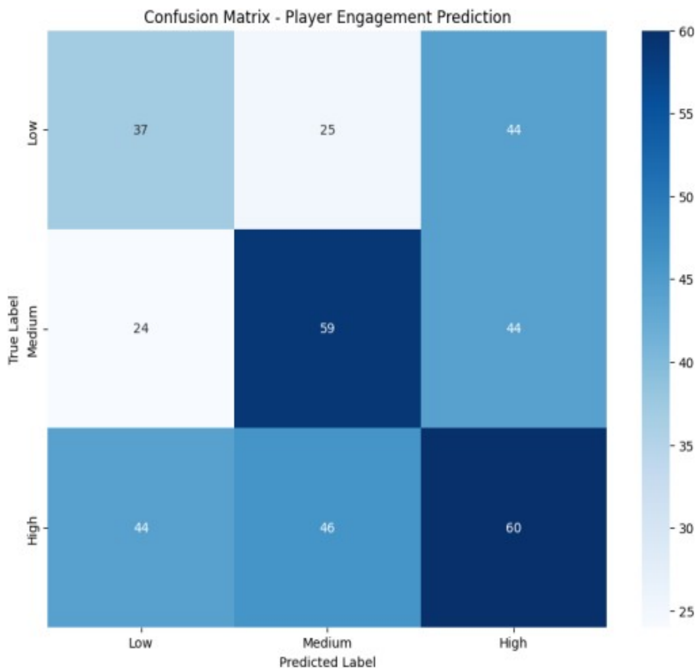

Figure 1: confusion matrix for player engagement prediction

High engagement is also frequently misclassified as Medium (46 times) or Low (44 times), showing the model has difficulty distinguishing high engagement from lower levels.

There's a notable number of misclassifications between Low and High across all true labels, highlighting a need to refine the model to better distinguish between these two extremes.

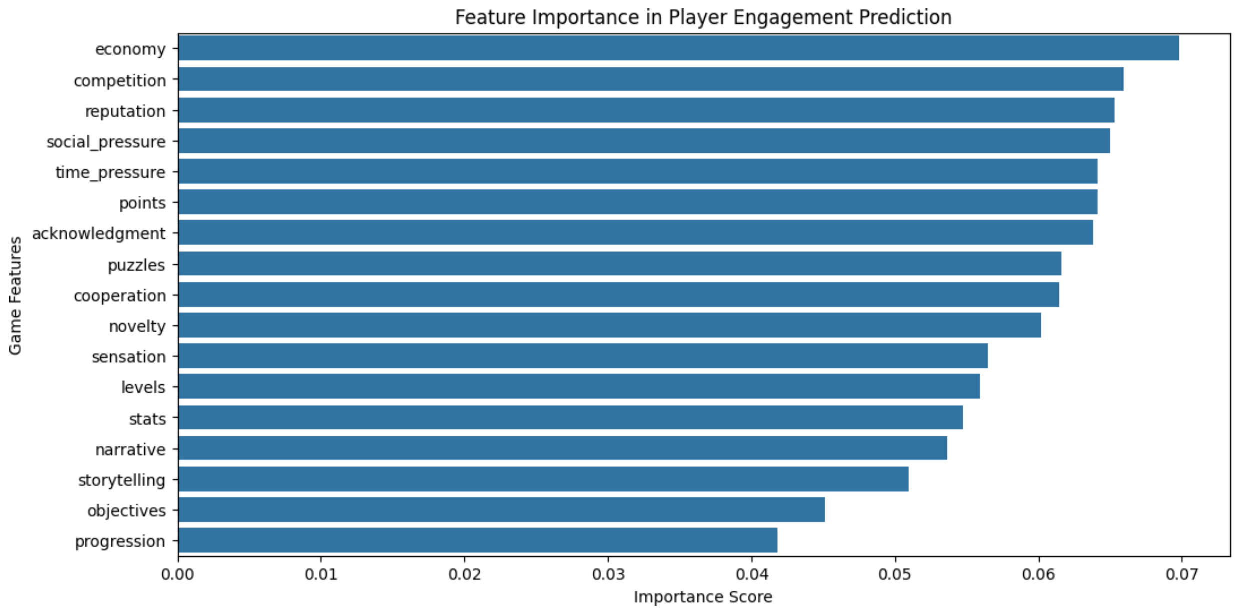

Figure 2: Importance score

Table 1 and Figure 2 highlights that game economy, competition, reputation, social pressure, and time pressure are the most significant factors in predicting player engagement, with economy scoring close to 0.07, which is highest.

Table 1
Top 5 most important features.

Feature:	Importance:
economy	0.0698

competition	0.0659
reputation	0.0653
social_pressure	0.0649
time_pressure	0.0640

These elements are critical in keeping players in the game, because they are related to in- game currency, competitive interactions, social status, peer influences, and timed challenges.

Lesser impact features such as points, puzzles, and storytelling have lower importance scores, suggesting that while they contribute to the gaming experience, they are not as influential in driving player retention.

Gamification platforms developers and game developers can enhance player engagement by focusing on these high-impact areas to ensure a more captivating and rewarding experience for users.

As from correlation between player demographics and engagement metrics, that represented by heatmap in Figure 3, age shows a negative correlation with both times spent playing weekly and points scored, meaning that older players engage less intensely than younger players.

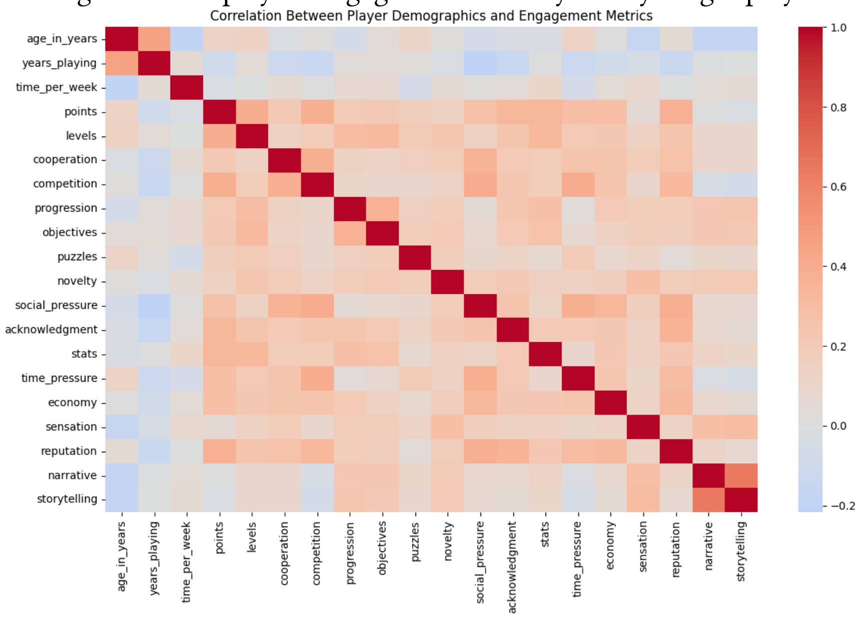

Figure 3: Correlation between player demographics and engagement metrics

Years of gaming experience positively correlate with higher scores and advanced levels, indicating that veteran players tend to perform better, as it should be. Social factors such as cooperation, competition, and social pressure are strongly linked to higher engagement metrics, highlighting their importance in keeping players invested. Additionally, elements like time pressure and novelty have strong positive correlations with player engagement, emphasizing the effectiveness of introducing new challenges and time-sensitive tasks to maintain player interest.

Figure 4 demonstrates the ROC (Receiver Operating Characteristic) curves for the random forest classifier to illustrate its performance across three engagement levels: Low, Medium, and High. The ROC curve for the medium engagement class (AUC = 0.64) indicates the highest performance, suggesting that the classifier is most effective in distinguishing this class.

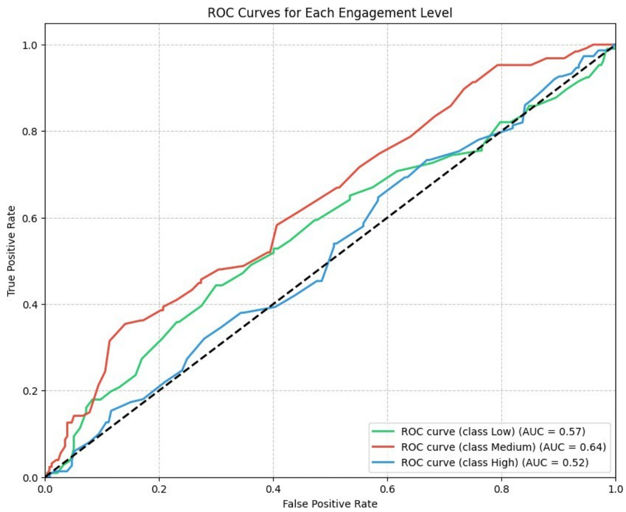

Figure 4: ROC curves for engagement levels for low, medium, high classes

The Low engagement class (AUC = 0.57) and High engagement class (AUC = 0.52) show lower performance, with the High class being the least accurately predicted. These AUC values reflect the classifier's ability to correctly identify true positives while minimizing false positives, with higher values representing better performance. The dashed black line represents the line of no-discrimination, serving as a baseline (AUC = 0.5). Overall, the random forest classifier performs best for the medium engagement level, providing insights into its diagnostic capabilities across different engagement categories.

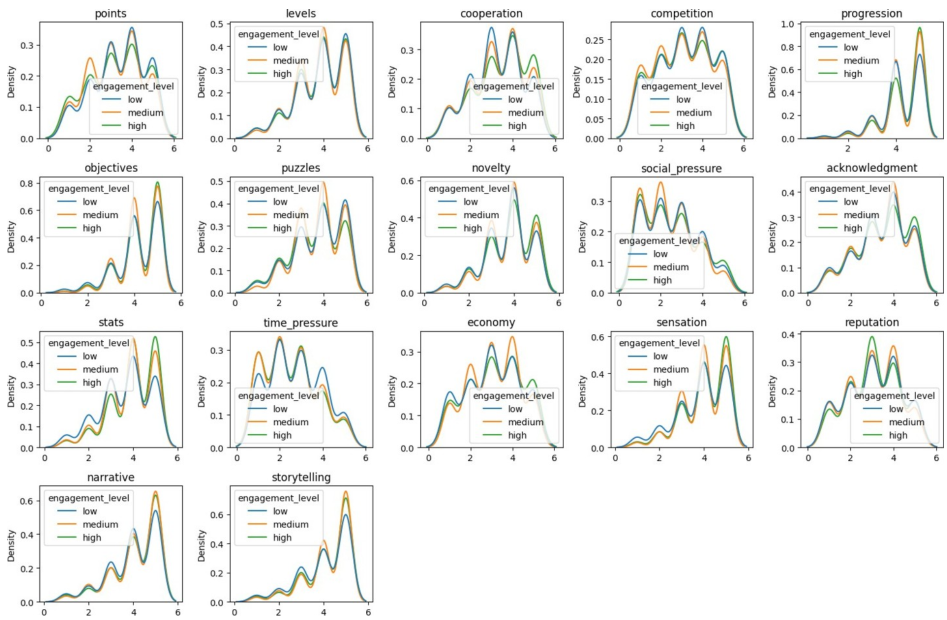

Figure 5: Distributions of all features

The density plots from figure 5 demonstrate the distribution of various game elements across three engagement levels: low, medium, and high.

Each plot shows how these elements, including points, levels, cooperation, competition, progression, objectives, puzzles, novelty, social pressure, acknowledgment, stats, time pressure, economy, sensation, reputation, narrative, and storytelling, are distributed among players with different engagement levels.

The x-axis represents a scale from 0 to 6 for each element, and the y-axis represents the density. Blue indicates low engagement, orange indicates medium engagement, and green indicates high engagement.

The plots reveal that players with high engagement (green) tend to have higher values in elements like points, levels, cooperation, competition, novelty, and time pressure compared to those with medium (orange) and low engagement (blue).

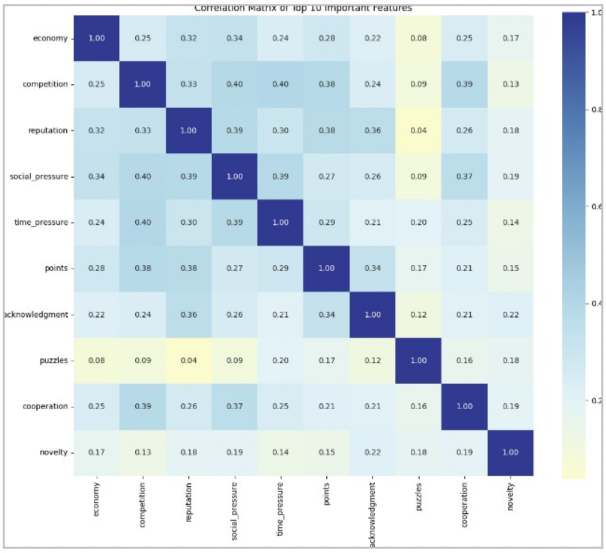

Figure 6: Correlation matrix of top 10 important features

As from figure 6, in which the correlation matrix for the top 10 important features is represented, strong positive correlations are observed between time pressure and competition as well as points and acknowledgment, highlighting how players, who feel pressured by time and enjoy competition, tend to score higher and recognize value. On the other hand, weaker correlations appear between economy and other features, suggesting that in-game economy elements may have a less direct impact on overall player engagement. This matrix is potentially a valuable tool for identifying features, that are closely related and can help game (or any other platform) developers.

5. Conclusions and prospects for further research

This study explored the impact of various gamification elements on player engagement using machine learning techniques. By analyzing the SAGE dataset, we identified key factors, such as game economy, competition, reputation, social pressure, and time pressure. They significantly influence engagement levels. Our findings suggest that these elements are crucial for designing engaging experiences, whether in education, marketing, or other interactive platforms.

The Random Forest model demonstrated its effectiveness in predicting engagement levels, particularly for medium-engagement users. However, the classification of low and high engagement levels showed room for improvement. Future research can improve these predictions by using advanced machine learning models or expanding the dataset to include other important behavioral insights.

Besides improving engagement, gamification combined with AI can potentially adapt learning experiences dynamically, changing game mechanics to individual needs, and even predicting potential challenges such as student disengagement. By implementing these insights, developers can design more engaging and satisfying gamified platforms, that prioritize which elements to enhance or modify to improve player experience and retention.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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