I-Mouse: A Framework for Player Assistance in Adaptive Serious Games

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Abstract: A serious game is an educational digital game created to entertain and achieve characterizing goal to promote learning. However, a serious game's major challenge is capturing and sustaining player attention and motivation, thus restricting learning abilities. Adaptive frameworks in serious games (Adaptive serious games) tackle the challenge by automatically assisting players in balancing boredom and frustration. The current state-of-the-art in Adaptive serious games targets modeling a player's cognitive states by considering eye-tracking characteristics like gaze, fixation, pupil diameter, or mouse tracking characteristics such as mouse positions. However, a combination of eye and mouse tracking characteristics has seldom been used. Hence, we present I-Mouse, a framework for predicting the need for player assistance in educational serious games through a combination of eye and mouse-tracking data. I-Mouse framework comprises four steps: (a) Feature generation for identifying cognitive states, (b) Partition clustering for player state modeling, (c) Data balancing of the clustered data, and (d) Classification to predict the need for assistance. We evaluate the framework using a real game data set to predict the need for assistance, and Random Forest is the best performing model with an accuracy of 99% amongst the trained classification models.

Keywords: Serious Games · Adaptivity · Eye and Mouse Tracking

1 Introduction

Serious Game (SG) is an entertaining tool for education. The main goal of SG is to promote learning besides entertainment by cultivating knowledge in players and allowing them to practice their skills through overcoming numerous obstacles in the game [13]. It is essential to maintain an efficient balance between motivation and boredom in SG. Adaptivity in SG is used to capture and process data to aid a player. These games are termed Adaptive Serious Games (ASG). According to Streicher and Smeddinck [11], personalization and adaptivity can promote motivated usage, increased user acceptance, and user identification in serious games. However, not assisting the player at the appropriate moment may lead to repetitive attempts by the player resulting in frustration, loss of interest, and hampering the player's progress. The current state-of-the-art utilizes various physical and behavioural biometrics like the player's eye-tracking data such as fixations, gaze, pupil size, or mouse-tracking data. Eye-tracking data can be used for cognitive load analysis [8], [12], [3], however, the effectiveness of the use of eye-tracking in computer games as a direct control input is questioned [1]. Khedher et al. [5] conclude that eye-tracking data is not the only indicator for cognitive load analysis. In the domain of cognitive state modeling using behavioural biometrics, Grimes et al. [4] show that mouse movement is also useful for cognitive load analysis.

In comparison with these adaptive studies and solutions, the I-Mouse framework incorporates eye-tracking and mouse-tracking to predict the need for assistance in SG. I-Mouse framework is equipped with (a) Data Preparation service to process the data (b) Feature creation service to create features from the eye and mouse tracking data (c) Partition clustering service to cluster different cognitive states (d) Data balancing service to balance the game data (e) Classification model creation service to predict instances when the player needs assistance.

2 I-Mouse Framework

As shown in Fig. 1, the I-Mouse framework comprises different services executed sequentially to perform a specific task. The orchestration of each service is coordinated by creating workflows using Apache Airflow[1].

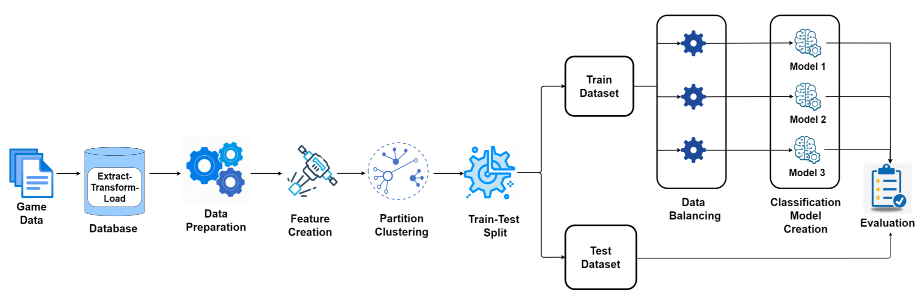

Fig. 1. I-Mouse Framework

I-Mouse framework uses the SaFIRa (Seek and Find for Image Reconnaissance adaptive) game data set collected by Streicher et al. [10]. The SaFIRa game data set comprises eye-tracking and mouse-tracking logs of twenty-four players with information about each player asking for assistance while playing the game. Assistance provided to the player is in the form of hints comprising of information regarding the distance remaining to reach the target and the direction in which the target lies. SaFIRa data set is divided into two classes, i.e.,

[1] https://airflow.apache.org/

"assistance required" and "assistance not required", with a high bias towards the "assistance not required" class. *Data Preparation* service's main functionality is to create a document-based database using SaFIRa dataset by executing Extract, Transform, and Load (ETL) jobs.

Grimes et al. [4] show that mouse position on screen does not have any relation to cognitive load. However, the frequency of mouse direction change is a good indicator of cognitive load. As the SaFIRa dataset records only mouse position, the *Feature Creation* service creates an additional mouse feature, i.e. Mouse Click Direction Change. The Mouse Click Direction Change is the total number of significant direction changes in 20 consecutive moves, where the direction changes are significant when direction changes by an angle greater than 90 degrees. This newly created feature, along with pupil size, fixation duration [8] [12] [3] helps to predict the player cognitive load.

After obtaining the new feature from the *Feature Creation* service, the *Partition Clustering* service is executed to form clusters of player cognitive states [7]. The *Partition Clustering* service uses the K-means clustering algorithm due to its scalability and time-efficiency compared to the K-Medoids clustering algorithm. The optimum k value representing the number of clusters obtained from the data set is determined using the elbow curve technique.

Due to the imbalanced distribution of classes in the SaFIRa data set, each cluster obtained from the *Partition Clustering* service is individually balanced for model training with the help of *Data Balancing* service. *Synthetic Minority Over-sampling Technique* (SMOTE) [2] for Over-sampling and *Random Under Sampling* [6] for Under-sampling is used for data balancing. A combination of SMOTE and Random Under Sampling is also considered to overcome both methods' limitations.

Considering the balanced data obtained after execution of *Data Balancing* service, *Classification Model Creation* service is executed to train the classification algorithm for predicting the need for player assistance. The *Classification Model Creation* service creates a classification model for every partitioned data set as it increases the framework's cumulative accuracy. Following are the five classification algorithms considered by this service: Logistic Regression (LR), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Decision Tree (DT), and Random Forest (RF).

3 Evaluation

We evaluate the I-Mouse framework by combining high, low, and normal cognitive load data sets. Data from the clustering service is split into train and test set using cross-validation technique to avoid over-fitting classification models [9]. Table 1 shows evaluation metric scores for different combinations of components present in the framework. The *Data Partition* column denotes whether the trained data is partitioned into different data sets based on the *Partitioning Clustering* service results, and *Data Balancing Technique* column denotes the data balancing technique used for the respective combination. The *Model* column denotes the classification algorithm used for the evaluation of the frame-

Table 1. Evaluation of I-Mouse Framework

Sr. No.	Data Partition	Data Balancing Technique	Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
1	No	Under Sampling	LR	89	89	99	0.93
2			LDA	97	88	73	0.80
3			QDA	80	80	76	0.75
4			DT	97	93	92	0.90
5			RF	98	99	86	0.92
6		Over Sampling	LR	98	89	99	0.93
7			LDA	93	88	73	0.80
8			QDA	78	83	76	0.76
9			DT	97	93	92	0.90
10			RF	98	99	86	0.92
11		Combination	LR	98	88	99	0.94
12			LDA	96	88	73	0.83
13			QDA	82	89	74	0.85
14			DT	96	98	83	0.88
15			RF	98	99	86	0.92
16	Yes		LR	93	61	93	0.65
17			LDA	87	66	93	0.68
18			QDA	93	61	90	0.75
19			DT	99	93	92	0.90
20			**RF**	**99**	**99**	**99**	**0.99**

work, and *Accuracy*, *Precision*, *Recall*, and *F1 Score* represents the evaluation metric scores for respective combination. The test data set contains 100,000 records with 91,646 records of the "assistance not required" class and 8,354 records of "assistance required" class. Test data are not passed through the data balancing service as test data emulates the real-world game data that is always imbalanced. The reason for high accuracy for most combinations is the data balancing techniques integrated during the model training process. Out of different combinations, the Random Forest classification model combined with data partition and combination of data balancing techniques is the best performing with an accuracy of 99%. This high accuracy value and the majority class's influence will be the subject of future in-detail studies.

4 Conclusion & Future Work

In this paper, we presented the I-Mouse framework that uses a combination of eye and mouse tracking data to predict the need for player assistance. I-Mouse framework is evaluated with different combinations of data sampling, data balancing, and classification algorithms. Out of different combinations, the Random Forest classification model combined with data partition and combination of data balancing techniques is the best performing with an accuracy of 99%. In our future work, we plan to replace cognitive state modeling with player state modeling leveraging a player's behavioural states and actions by employing the Hidden Markov Model (HMM) and Reinforcement Learning.

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