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Implementation of Elo Rating System and Player Clustering for Competitive Matchmaking in Trivia Education Game

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ABSTRACT

Multi-player online games have a matchmaking system, where two or more players can meet each other in a virtual room [19][20]. Players do not gain competitive experience when the matchmaking system uses a single parameter because the system cannot recognize players properly. Previous studies carried out several matchmaking methods, namely skill-based, behavior-based, role-based, and latency-based. However, few studies have discussed the computation of multi-parameter aggregation. We propose a matchmaking system that combines three essential things that become competitive matchmaking parameters: skill rating, behavior cluster, and location cluster. The Elo rating system will use to measure player ability. It will combine with player behavior clustering and player location clustering. It combines a statistical approach to managing distributions and unsupervised machine learning to identify players. Grouping players with machine learning methods is a new thing that has been researched in recent years [6][8]. The application of the algorithm with these parameters is carried out on the trivia education game to make it more competitive.

1. Introduction

Game player behavior analysis is a long-term issue with respect to game design, development, and marketing [1]. The government through BEKRAF also encourages creative economic growth through young creators in various fields. According to a report from BEKRAF (now KEMENPAREKRAF), the creative *game* industry is developing well in Indonesia due to many factors, including; the tendency of changes in people's interest in this type of game from being traditional to a game with a more modern form and relying on technology [2]. In mid-2018, the Association of Indonesian Internet Service Providers (APJII) released that currently more than 143 million Indonesians have become active internet users, this has exceeded 50% of the Indonesian population of around 260 million [3]. This is also supported by the APJII survey in 2019-2020, which concluded that around 16.5% of internet users use the internet to play games [4]. The behavior of the Indonesian people when they are in the game is an important thing to study in online multiplayer games, education, gamification, simulations and others. Developers should have access to detailed player activities [5].

In recent years game analysis can be done with several approaches. Among them with game analytics tool integration [5]. In online multiplayer games there is a matchmaking system, where two or more players can meet each other in a virtual room [19][20]. The matchmaking system can be divided into 2, namely traditional and modern. The traditional matchmaking system is done by manually creating a virtual room by the host, then other players join the room. Modern matchmaking relies on automatically computing servers, selecting and entering players into virtual spaces. This research is expected to produce progress from traditional analysis patterns to knowledge discovery. Finding patterns of player activity using an unsupervised learning

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approach. From the results of the clustering of player activities combined with geospatial tracking, it can produce an analysis platform system design for matchmaking services [21].

2. Method

2.1 Design System

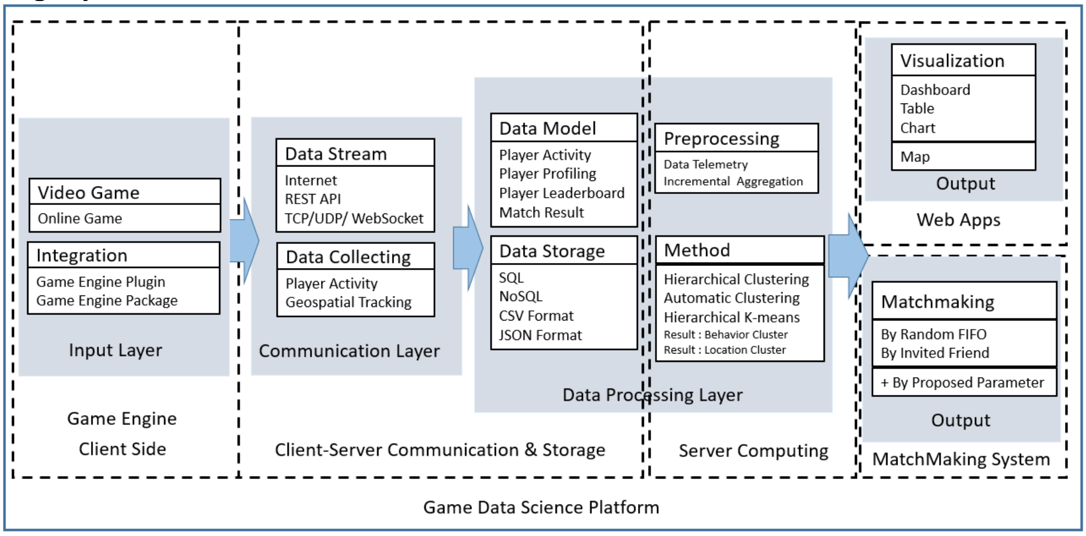

Fig 1. Design System

Figure 1. Game telemetry can be done by integrating the game engine with the backend API through packages or plugins. The Game Data Science API is used to store player activity and match results. The Photon Unity Networking API is used to perform realtime communication when playing in online multiplayer mode. The mobile game genre online multi-player quiz was created using the Unity game engine, but it is possible that this framework can be implemented using various other game engines such as Construct and Unreal. This is because the REST API integration can reach all game engines as long as it can communicate with the HTTP protocol.

Data that has been sent via the API and then stored into the database can use the Relational Database Management System SQL, besides that there is also a NoSQL Database key-value store to cache dashboard user sessions. The data set will be issued in CSV and JSON format for further processing to the preprocessing stage.

Initially the challenge of preprocessing was that every time aggregation wanted to produce a cluster on the server side, this was because the activities carried out by players caused the value of the feature to continue to grow. However, in the end, a preprocessing solution was taken which was carried out on the client side, namely the background process in the game. The device used by the player will process the calculation of activity and match results, so the server only needs to receive data without the need for reprocessing. This is done to save computational costs and the time required to generate player cluster numbers.

This study uses a video game quiz trivia media in the internet network. In the video game that will be designed, there are 4 play modes and 9 question topics.

Table 1.
Trivia Topics & Play Mode

Topic	Mode	Description	Total Questions
General Knowledge	1,2,3,4	All topics combined	50
Math	1,2,3,4	Arithmetic	50
Nature	1,2,3,4	Nature / Science	50
History	1,2,3,4	Historical Knowledge	50
Geography	1,2,3,4	Geography Knowledge	50
Covid19	1,2,3,4	Knowledge of Covid19	50
Sport	1,2,3,4	Popular sports knowledge	50
Pop Culture	1,2,3,4	Entertainment knowledge	50

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Description in table 1, Mode : 1. Offline Single-player - True or False Question (TFQ), 2. Offline Single-player - Multiple Choice Question (MCQ), 3. Online Multi-player - True or False Question (TFQ) , 4. Online Multi-player - Multiple Choice Question (MCQ).

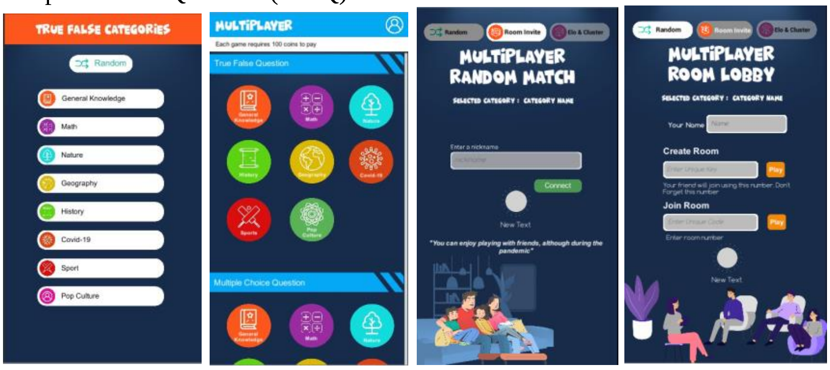


Fig 2. Trivia Education Games (Multiplayer Online Game)

Figure 2. From left, Game display when selecting topic in offline true or false quiz mode. Then choose a topic in online play mode. Then enter the random matchmaking & invitation room method. Each training session is in offline mode and the results of online matches are sent to the database server. Then enter the clustering stage. At this stage, it is necessary to do a cluster analysis to determine the quality of the cluster.

Cluster analysis was conducted to test the performance of the clustering algorithm. Determination of the ideal cluster can be done by moving variance analysis according to the supporting theory, namely valley tracing. The algorithm used to determine the ideal number of clusters is automatic clustering. Automatic clustering can be used to group player activities automatically because it is difficult to determine the number of clusters. The k-means clustering algorithm is considered less effective in getting the best cluster quality. This happens due to the inability to get the most appropriate number of iterations in the cluster division process. Hierarchical K-means offers basic k-means optimization by optimizing the centroid generation to measure how far the player data is from the midpoint.

From the results of clustering, data from players can be grouped into several clusters. The clustering carried out in this study must be done automatically by the system, so that grouping can be done dynamically when dataset changes occur. From the results of this cluster can be used as a combination of parameters to determine a commensurate opponent.

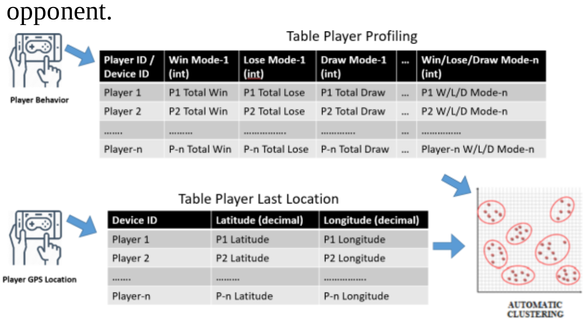
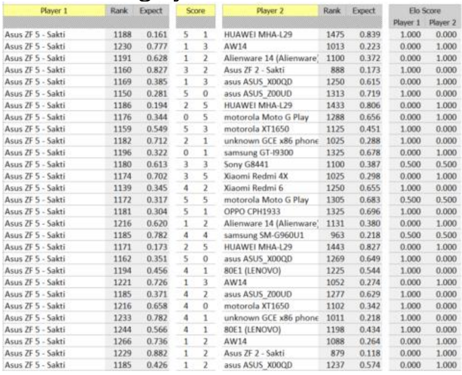


Fig 3. Illustration of clustering for matchmaking

According to Figure 3, the input of player activity is aggregated, then a dataset is obtained for each player profile. The first parameter of the matchmaking system is the similarity of the player's activities, in general the attributes used are win, lose, draw because they represent the results of the player's achievements. While the second parameter is the location of the player which is calculated from latitude and longitude. After players are grouped into each cluster, then players can meet other players if they are in the same cluster and vice versa. Based on these 2 parameters, it produces a system that can solve the problem of unbalanced matchmaking.

3. Result and Analysis

3.1. Elo Rating System



Player 1	Rank	Expect	Score		Player 2	Rank	Expect	Elo Score Player 1	Elo Score Player 2
Asus ZF 5 - Sakti	1188	0.161	5	1	HUAWEI MHA-L29	1475	0.839	1.000	0.000
Asus ZF 5 - Sakti	1230	0.777	1	3	AW14	1013	0.223	0.000	1.000
Asus ZF 5 - Sakti	1191	0.628	1	2	Alienware 14 (Alienware	1100	0.372	0.000	1.000
Asus ZF 5 - Sakti	1160	0.827	3	2	Asus ZF 2 - Sakti	888	0.173	1.000	0.000
Asus ZF 5 - Sakti	1169	0.385	1	3	asus ASUS_X00QD	1250	0.615	0.000	1.000
Asus ZF 5 - Sakti	1150	0.281	5	0	asus ASUS_Z00UD	1313	0.719	1.000	0.000
Asus ZF 5 - Sakti	1186	0.194	2	5	HUAWEI MHA-L29	1433	0.806	0.000	1.000
Asus ZF 5 - Sakti	1176	0.344	0	5	motorola Moto G Play	1288	0.656	0.000	1.000
Asus ZF 5 - Sakti	1159	0.549	5	3	motorola XT1650	1125	0.451	1.000	0.000
Asus ZF 5 - Sakti	1182	0.712	2	1	unknown GCE x86 phone	1025	0.288	1.000	0.000
Asus ZF 5 - Sakti	1196	0.322	0	1	samsung GT-I9300	1325	0.678	0.000	1.000
Asus ZF 5 - Sakti	1180	0.613	3	3	Sony G8441	1100	0.387	0.500	0.500
Asus ZF 5 - Sakti	1174	0.702	3	5	Xiaomi Redmi 4X	1025	0.298	0.000	1.000
Asus ZF 5 - Sakti	1139	0.345	4	2	Xiaomi Redmi 6	1250	0.655	1.000	0.000
Asus ZF 5 - Sakti	1172	0.317	5	5	motorola Moto G Play	1305	0.683	0.500	0.500
Asus ZF 5 - Sakti	1181	0.304	5	1	OPPO CPH1933	1325	0.696	1.000	0.000
Asus ZF 5 - Sakti	1216	0.620	1	2	Alienware 14 (Alienware	1131	0.380	0.000	1.000
Asus ZF 5 - Sakti	1185	0.782	4	4	samsung SM-G960U1	963	0.218	0.500	0.500
Asus ZF 5 - Sakti	1171	0.173	2	5	HUAWEI MHA-L29	1443	0.827	0.000	1.000
Asus ZF 5 - Sakti	1162	0.351	5	0	asus ASUS_X00QD	1269	0.649	1.000	0.000
Asus ZF 5 - Sakti	1194	0.456	4	1	80E1 (LENOVO)	1225	0.544	1.000	0.000
Asus ZF 5 - Sakti	1221	0.726	1	3	AW14	1052	0.274	0.000	1.000
Asus ZF 5 - Sakti	1185	0.371	4	2	asus ASUS_Z00UD	1277	0.629	1.000	0.000
Asus ZF 5 - Sakti	1216	0.658	4	0	motorola XT1650	1102	0.342	1.000	0.000
Asus ZF 5 - Sakti	1233	0.782	4	1	unknown GCE x86 phone	1011	0.218	1.000	0.000
Asus ZF 5 - Sakti	1244	0.566	4	1	80E1 (LENOVO)	1198	0.434	1.000	0.000
Asus ZF 5 - Sakti	1266	0.736	1	2	AW14	1088	0.264	0.000	1.000
Asus ZF 5 - Sakti	1229	0.882	1	2	Asus ZF 2 - Sakti	879	0.118	0.000	1.000
Asus ZF 5 - Sakti	1185	0.426	1	2	asus ASUS_X00QD	1237	0.574	0.000	1.000

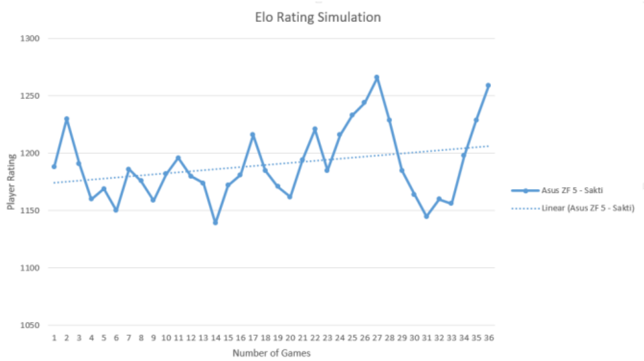


Fig 4. Simulation of Elo Rating System

Figure 4 (Left) is a dataset of the simulation process for calculating the player's rating. From the simulation results, it can be observed that the elo rating helps the balancing process. The balance point in the game is what developers and players are looking for. The point of balance should provide fairness in the assessment and determination of results. Furthermore, this algorithm is fair in dividing the match points. For example, it can be seen from the graph in Figure 4 (right), explaining that the rating of players has increased significantly when they have defeated opponents with far high experienced players (top ratings). Vice versa, if you lose by a new player opponent is far below (lower rating) then you will lose significant points. So that when you get an opponent with a commensurate rating, the change in points will tend to be gentle and propagate slowly. Changes in points up and down gently and slowly creeping are proof of a more competitive game.

3.2. Player Clustering

Table 2.

Results of Clustering Behavior (last dataset)

Player Name / Device	SLHAC	ALHAC	ComLHAC	CenLHAC
80E1 (LENOVO)	1	0	0	11
Alienware 14 (Alienware)	1	0	0	0
asus ASUS_X00QD	1	0	0	11
asus ASUS_Z00UD	3	3	4	13
Asus ZF 2 - Sakti	0	1	2	3
Asus ZF 5 - Sakti	5	2	2	9
AW14	6	3	3	12
HUAWEI MHA-L29	3	3	4	13
motorola Moto G Play	1	0	1	11
motorola XT1650	4	1	2	4
OPPO CPH1933	9	0	1	5
PC	2	0	3	7
samsung GT-I9300	9	0	1	7
samsung SM-A510F	1	0	0	10
samsung SM-G960U1	9	0	1	6
Sony G8441	1	0	0	0
unknown GCE x86 phone	1	0	0	8
Xiaomi Redmi 4X	9	0	1	1
Xiaomi Redmi 6	1	0	0	2

Table 2 shows the results of clustering based on behavior using the hierarchical k-means method to divide the player population into several groups [33]. The best clustering is done with the distance complete linkage method, because each individual player at least gets an opponent to play. This is an exception for players who are detected as outliers who are the only members.

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Table 3.
Results of Clustering Location (last dataset)

Player Name / Device	SLHAC	ALHAC	ComLHAC	CenLHAC
80E1 (LENOVO)	3	0	3	1
Alienware 14 (Alienware)	0	3	0	3
asus ASUS_X00QD	0	1	2	0
asus ASUS_Z00UD	0	1	2	0
Asus ZF 2 - Sakti	0	3	0	3
Asus ZF 5 - Sakti	0	3	0	3
AW14	0	1	2	0
HUAWEI MHA-L29	0	1	2	0
motorola Moto G Play	0	1	2	0
motorola XT1650	0	1	2	0
OPPO CPH1933	0	3	0	3
PC	0	1	2	0
samsung GT-I9300	0	4	0	4
samsung SM-A510F	2	5	1	5
samsung SM-G960U1	1	2	1	2
Sony G8441	0	4	0	4
unknown GCE x86 phone	0	3	0	3
Xiaomi Redmi 4X	0	1	2	0
Xiaomi Redmi 6	0	3	2	3

Table 3 shows the results of clustering by location. Location clustering can show how dense the player population is based on location. The best results are single linkage distance method on hierarchical k-means [33]. The results show that a relatively close range of locations can be done so that it is not too rigid in group restrictions. We need a larger population coverage of cluster behavior for each cluster number, so that the location parameter can corroborate the results of cluster behavior. It also determines the network latency that may occur if players meet despite having different clusters. The system will automatically search for nearby players to minimize network latency.

Table 4.
Proposed Parameter

Parameter	Type	Description
Elo Rating System	Statistics Distribution	Rating players' abilities using statistical methods to calculate skill representation fairly.
Behavior Cluster	Unsupervised Learning	Grouping players based on playing habits which shows how experienced the player is based on playing activities.
Location Cluster	Unsupervised Learning	Grouping players by location to find out how close the distance between players in the real world is, is a consideration of network latency.

4. Conclusion

We propose a hybrid matchmaking parameter based on the parameters in table 4. Elo rating is used to calculate player abilities (skill-based). Cluster behavior groups players based on behavior (behavior-based), and location calculates the closest distance to avoid network latency (location-based). It is a hybrid method that combines Elo Rating and clustering, which is a statistical distribution approach that meets unsupervised machine learning. The robustness of machine learning methods has been proven in several cases of solving big data analysis. So that by combining these three parameters, it is inevitable that the system will comprehensively provide the best performance in the matchmaking process without being constrained by the growing player population in Elo Rating.

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