Next Level Matchmaking

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ABSTRACT

Matchmaking is a matching process. In game, those matchmaking is a matching process that functions to find our opponents and friends. However it is harder to win the game when there are smurf players who play in matches that don't match their abilities. Because of that, we want to propose next level matchmaking. We choose OptMatch as our dataset and implement K-Nearest Neighbout to player in real matchmaking.

Keywords: *Matchmaking, Game, Smurf, Multiplayer, Player.*

1. INTRODUCTION

Matchmaking is a matching process. Matchmaking is commonly used in dating apps and games, here we will discuss about Matchmaking in the game. Matchmaking itself, which we mentioned earlier, is a matching process that functions to find our opponents and friends. In Matchmaking there is an algorithm that can determine who our opponents are and who are our teammates based on existing data.

The games that are our focus in implementing this matchmaking are MOBA-type games such as Mobile Legend, League of Legends, Dota 2 and other MOBA games. We chose the MOBA type game because the team search system in the MOBA game is more complicated than other games because in the MOBA game there are many roles that must be fulfilled to be able to win the game, while most of the teams that are obtained often use the same role so there are roles that are not fulfilled in the game. one team in particular when we play with random players.

Not fulfilling all roles in one team makes the game difficult to win so that players don't get pleasure in playing, especially when there are smurf players who play in matches that don't match their abilities, that's why we are doing research on next level matchmaking.

What is next level matchmaking? Next level matchmaking is a more advanced matchmaking that matches based on many aspects such as how the player performs in the game, what roles are often used in matches, account creation dates, and in-game statistics, so matchmaking is not only based on rank in the game. So that you can avoid players from smurf players whooften deliberately reduce their rank to get easy enemies and avoid players who play with random people getting a team with a messy composition.

2. LITERATURE REVIEW

Matchmaking is an important issue in online gaming. One of the problems that players often experience in games is meeting smurf players and random teams that don't match us. Playing with random players sometimes makes us unable to work together so it makes us frustrated.

Matchmaking now cannot distinguish smurf players because the system can only differentiate between ranks and also cannot differentiate between teams that are suitable for us, so our group aims to study the interactions between increased performance between players who play throughout the game by looking at developments in the game by counting power between players.

To lure smurf players, we can use the help of the DDA method because usually smurf players will definitely use a different account so that the DDA method is made to adjust the skills read through analysis to balance the composition of a team that will play.

Development can occur according to the existing template using HCG balancing in the case of selection and sorting. Matchmaking uses the rankings of players to perform similarly to other players. Matchmaking must also adjust to real time because it is in the same matchmaking so when doing it must be fast and precise.

Having a good team and not meeting smurf players will definitely increase the enjoyment of each player in the game, with this it can also balance the differences between ranks so that there is no one-sided game.

We as developers definitely want all the players to play comfortably and not only benefit one player so that the games we make are played more and more because usually making games requires a relatively large investment. With such investments we as developers definitely design not only good designs but also good rules for all players. With both, our game will be more comfortable to use and there will be more players.

A game must have a profile that is needed for the needs of a game. With that the profile must have game data on the player. In this matchmaking we can identify existing anomalies by cursing this profile. In this profile, there will be a credit score that allows us to identify whether this player is normal or there is an anomaly (smurf). With this profile, we can also see what players are doing in playing this game, whether it's normal or an anomaly.

With a profile in a game, of course, it is also very helpful in collecting information and data on a player in raising the existing level in different ways depending on the player. With this, it's hard to tell which players are normal and smurfs. To determine this, it must have a level such as a credit score that exceeds the limit then he is already considered an anomaly player.

From research by Hao Wang, it shows a new way to make matchmaking with more profitable matches to all existing players with different criteria from player methods, credit scores, and others that make matchmaking fairer than the old matchmaking. In this research created from a small survey of players who enjoy the new matchmaking by revealing that the old matchmaking was not good.

With a successful credit score for Smurf players through individual skills, this will cause the matchmaking to be used to be better, especially by building new knowledge matchmaking models based on experts. Some of this research was influential in limiting the effect of matchmaking and analyzing all existing players through existing profiles in future matchmaking experiments. By describing individual abilities and feedback from players, Smurf players will be easy to find in a pattern.

Even though the game is fair, it is possible that not all players can enjoy the game that we have made, the new matchmaking is more fair. It's possible that there are players who don't smurf but have really good skills, they won't be happy if they are reported by other people which causes their credit score to decrease and can't do matchmaking. But it would be good if the smurf player who actually used the smurf account would be banned, it would create a certain satisfaction for the player who fought the smurf player, an online game should have fair matchmaking that makes the players enjoy the game. been made at great expense. Matchmaking will actually make a big deviation between players who have good skills and those who don't.

3. METHODOLOGY

The methodology that will be used to improve matchmaking is getting better, it must have criteria such as fairness so that each team that competes has equality between the teams and players.

$s(X) = \sum x \in X \;\; sx$

With this smurf, it is possible that a team without smurf players will experience a crushing defeat (no resistance) because it is different in terms of gameplay and player skills. So it is very necessary to identify whether a player is a smurf or not when doing matchamaking.

Usually matchmaking uses many methods such as Elo, Glicko and True skill to do good matchmaking, but this has been since 1978 players are getting smarter to do cunning to get the win. But elo is still good to use because of its performance to distribute variables randomly by looking at the player's skills in real. This is usually used to determine the existing rankings of the players, if the players win continuously then the players will get higher in rank and if they lose the rank will go down. With matchamaking, you really need a rank that can make a game have good fairness.

For our analysis we use dataset from OptMatch: Optimized Matchmaking via Modeling the High-Order Interactions on the Arena (2020). We choose this because in online game so many player smurf in Multiplayer Online Battle Arena Video Games like Dota, and LOL. Dota2, LOL(League of Legends) are datasets of the famous 5v5 Multiplayer Online Battle Arena (MOBA) games, in which players control heroes of different abilities to fight. Dota2 contains 50,000 matches, 113 heroes and 10,815 players. LOL(League of Legends) contains 187,588 matches, 139 heroes and 43,706 players. We use evaluation matricst know only binary result marks(win/loss) available accuracy(Acc) is used to measure the models.

Machine learning start from pattern recognition and theory that machine can learn by themselves to do any specific task to improve the matchmaking in Dota . Example for how to pick the appropriate players to form a team from a pool of queuing players. The more data that use to feed the model then the machine learning can do better then before. We made machine learning for avoid smurfing in matchmaking is report from another player that play with smurf in same matchmaking. So the model can know that is smurf or real player that queue in the game. If the player is a smurf, player will be penalized.

Not only report from other player, smurf have a different graph from other players in the real rank.

For the profiles of players who follow the existing matchmaking from credit scores, each profile must have data the players see for example Dota 2, namely there is Gold per minute, EXP per minute, Damage to towers, Damage to heroes, How many do towers, Kill, Death, Assists, and skills of these players reported by other players. With this data, the model that has been made will be identified to see if this player is normal or anomaly. Not only that, the credit score is also very influential in seeing whether this player anomaly or not, the players who don't smurf will be identified fairly. 2 This method is effective for this new matchmaking.

Using K-Nearest Neighbor is finding a shortest path between the data to be evaluated and its K-nearest neighbors in the training data to maintain each rank of player in real matchmaking. To evaluate how smurf can easily know by system we made credit score, that maintain another player can report smurf that effect to their credit score.

4. RESULTS

In this final stage, we will explain some of the results that we get from the matchmaking system research. This will explained that the stage of realizing of the results of the design into an application that can be operated in order to achieve results in accordance with the design.

After collecting variable data and the stage of system design and software implementation, then calculations using the K-Nearest algorithm, the next action is the application of the software results. Here are some of the results that have been obtained:

4.1 Input page

This page is a page for entering data from players who want to see the classification of their account. Here the user must enter their account data, including, Nickname, Rank, Number of Matches, Win Rate, KDA, Total Match Number, Overall Win Rate, Overall KDA, and Credit Score.

4.2 New player

On this page, the data that has been input on the input form will be displayed in the form of a table.

4.3 Data sample

In this case, there is sample data that will be used as test data for the new data.

- Matchmaking

On this page, the data from the user account and also the data from the sample data are displayed again. However, the data shown is only Nickname, Rank, Number of Matches, Win Rate, and Credit Score.

4.4 Matchmaking result

On this page, it will be displayed the result of the calculation of proximity value between user data and sample data. The value shown is a percentage of proximity between user data and sample data. The calculation method is:

4.5 KNN Algorithm

1. Specifies parameter K as the number of neighboring closest to the new object.
2. Calculate the distance between new objects/data against all objects/data that have been trained.
3. Sort the results of the calculation.
4. Specify the nearest neighbor based on the minimum distance to K.
5. Specify the category of the closest neighbor to the object/data.
6. Use the majority category as the new object/data classification.

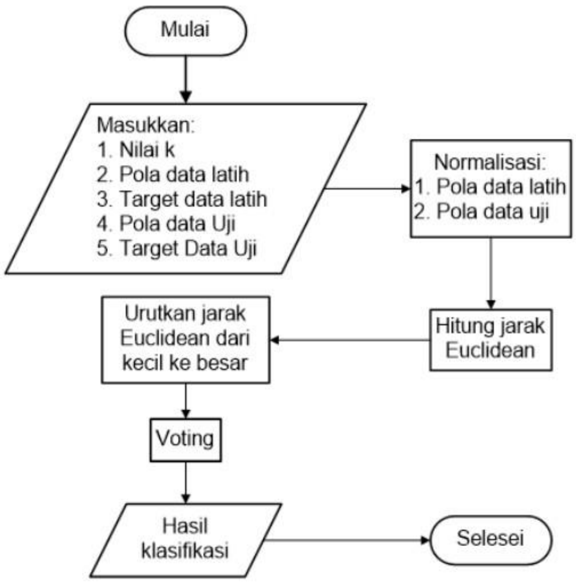

Figure 1 KNN Flowchart.

5. CONCLUSION

Today many people are using the account smurf and it makes the game becomes a draw and therefore the presence of Next Level Matchmaking we'll make the match will be much more balanced by using some test data such as how quickly people that produce gold per minute, damage to hero per minutes, tower damage per minute, average kill, average assist, and average death. That will be our data to make Next Level Matchmaking and it will make the game more fair. With all existing data we will use K-Nearest Neighbor to find the shortest path between the data to be evaluated.

REFERENCES

[1] Xu, Mingxuan, Yu, Yang, Wu, Chenye. (2019). Rule Designs for Optimal Oline Game Matchmaking. Ithaca, New York: Cornell University. Diakses dari https://arxiv.org/abs/1911.11852

[2] Sarkar, Anurag, Williams, Michaels, Deterding, Sebastian, Cooper, Seth. (2017). Engagement Effects of Player Rating System-Based Matchmaking for Level Ordering In Human Computation Games. Boston, United State: Northeastern University. Diakses dari https://dl.acm.org/doi/pdf/10.1145/3102071.3102093

[3] Kuipers, Wietse. (2019). Improving Matchmaking with Game Data. Gelderland, Netherland: Computer Science, Radboud Unversity. Diakses dari https://www. cs.ru.nl/bachelors- theses/2016/Wietse_Kuipers 4317904 Improving_matchmaking _with_game_data.pdf

[4] Gong, Linxia, Feng, Xiaochuan, Ye, Dezhi, Li, Hao, Wu, Runze, Tao Jianrong, Fan, Changjie, Chui, Peng. (2020). Opt Match: Optimized Matchmaking via Modeling the High-Order Interactions on the Arena. Hangzou, China: Tsinghua University. Diakses dari https://dl.acm0.org/doi/pdf/10.1145/3394486.34032794

[5] Alman, Josh, McKay, Dylan. (2017). Theoretical Foundations of Team Matchmaking. Cambridge, United Kingdom: Computer Science and Artificial Intelligence Laboratory Massachusetts Institute of Technology. Diakses dari ifaamas.org/ Proceedings/ aamas2017/ pdfs/p1073.pdf

[6] Gui, Xinning, Kou, Yubo. (2018). Entangled with Numbers: Quantifed Self amd Others in a Team-Based Online Games. Philadelphia, United State: Pennysylvania State University. Diakses dari https://dl.acm.org/doi/ pdf/10.1145/3274362

[7] Sarkar, Anurag, Cooper, Seth. (2018). Meet your Match Rating: Providing Skill Information and Choice in Player-Versus-Level Matchmaking. Boston, United State: Northeastern University. Diakses dari https://dl.acm.org/doi/10.1145/3235765.3235795

[8] Hou, Chin Wing. (2018). Behavior-Based Matchmaking System Using Player’s Traits Classification. Perak, Malaysia: Faculty of Information and Communication Technology (Perak Campus) Universiti Tunku Abdul Rahman. Diakses dari http://eprints.utar.edu.my/3038/1/fyp_CS_2018_CWH_-_1500533.pdf

[9] Idungima, Edidiong, Uko. (2017). Development Of Multi-Person Multi-Attribute Matchmaking Decision System. Durban, South Africa: Departement of Information Technology Faculty of Accounting and Informatics Durban University of Technology. Diakses dari https://openscholar.dut.ac.za/bitstream/10321/2933/1/UKO_EI_2017. pdf

[10] Xueting Wang , Q.Z. (2018). Matching game based resource allocation algorithm for energy-harvesting small cells network with NOMA.

[11] Samar Shaker Metwaly, A.M.A.E.H. (2020). NOMA Based Matching Game Algorithm for Narrowband Internet of Things (NB-IoT) System.

[12] Bouchaib Assila, A.K. (2018). Achieving low-energy consumption in fog computing environment: A matching game approach.

[13] Xiaozhu Liu, R.Z. (2016).Dynamic Spectrum Access Algorithm Based on Game Theory in Cognitive Radio Networks.

[14] M. K. Elhattab, M.M. (2019).Device-Aware Cell Association in Heterogeneous Cellular Networks: A Matching Game Approach.

[15] Samar Shaker Metwaly, A.M.A.E.H. (2021).No-Regret Matching Game Algorithm for NOMA Based UAV-Assisted NB-IoT Systems.

[16] Xueting Wang, Q.Z. (2018).Matching Game Based User Access Algorithm in Energy-Harvesting Small Cell Network.

[17] Bouchaib Assila , A.K. (2018).Achieving low-energy consumption in fog computing environment: A matching game approach..

[18] Xin Shi , D.W. (2019).Resource Allocation for Covert Communication in D2D Content Sharing: A Matching Game Approach.

[19] Shang, F., Zhou, D., & He, D. (2020). An admission control algorithm based on matching game and differentiated service in wireless mesh networks. Neural Computing and Applications, 32(7), 2945-2962.

[20] Jia, Z. H., Pan, L., Liu, X., & Li, X. J. (2021). A novel cloud workflow scheduling algorithm based on stable matching game theory. The Journal of Supercomputing, 1-28.

[21] Pham, C., Tran, N. H., & Hong, C. S. (2017). Virtual network function scheduling: A matching game approach. IEEE Communications Letters, 22(1), 69-72.

[22] Abouaomar, A., Kobbane, A., & Cherkaoui, S. (2018, December). Matching-game for user-fog assignment. In 2018 IEEE Global Communications Conference (GLOBECOM) (pp. 1-6). IEEE.

[23] Liu, D., Xu, Y., Xu, Y., Ding, C., Xu, K., & Xu, Y. (2016). Distributed satisfaction aware relay assignment: a novel matching game approach. Transactions on Emerging Telecommunications Technologies, 27(8), 1087-1096.

[24] Kazmi, S. M. A., & Hong, C. S. (2017, January). A matching game approach for resource allocation in wireless network virtualization. In Proceedings of the 11th International Conference on ubiquitous information management and communication (pp. 1-6).

[25] Michał, B., Jerzy, B., & Anna, K. (2020). P2P matchmaking solution for online games. Peer-To-Peer Networking and Applications, 13(1), 137-150.

[26] Myers, D. (2019). Matchmaking games and art: What's the best fit?. In Double Game Philosophy Conference Proceedings.

[27] Schuh, S. (2020). Psychological Matchmaking for Teams in Games.

[28] H. Wang, H. T. Yang, and C. T. Sun. Thinking Style and Team Competition Game Performance and Enjoyment. In: IEEE Transactions on Computational Intelligence and AI in Games 7.3 (Sept. 2015), pp. 243– 254. issn: 1943-068X. doi: 10.1109/TCIAIG.2015.2466240