BEHAVIOR-BASED MATCHMAKING SYSTEM USING PLAYER'S TRAITS CLASSIFICATION

By

CHIN WING HOU

A REPORT

SUBMITTED TO

University Tunku Abdul Rahman

in partial fulfilment of the requirements

for the degree of

BACHELOR OF COMPUTER SCIENCE (HONS)

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UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF INFORMATION & COMMUNICATION TECHNOLOGY (PERAK CAMPUS)

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ABSTRACT

Matchmaking is a process that distributes players into appropriate teams from a big pool of players in gamming sessions. Dota2 use skills-based matchmaking system to put players into teams which put players with equal skills level together into teams. Players will likely to encounter teams that have unbalanced roles. This project proposes a traits-based matchmaking system to distribute players into teams. Player's role-based matchmaking system is a matchmaking system that put players into teams according to their roles in the games. This mean that teams created by the matchmaking system will have balanced roles.

A profiling algorithm is created to make a profile that can show the personal traits of a person for each player. The profiling algorithm will consist of data mining method that can gather data from players after each game. The data then is used to describe the player's behaviors through the profile. A traits-based matchmaking algorithm is created to groups players together using the player's profile. A universal evaluation system is created to evaluate that the traits-based matchmaking system is more effective than skills-based matchmaking system using match reports statistical analysis.

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LIST OF ABBREVIATIONS

MMO	Massive Multiplayer Online
MMORPG	Massive Multiplayer Online Role-Playing Game
PVP	Player-versus-Player
PVE	Player-versus-Environment
DOTA2	Defense of The Ancients 2
LOL	League of Legends
SABAF	Sequence Alignment-based Behavior Analysis Framework
HDFS	Hadoop Distributed File System
ERGM	Exponential Random Graph Models
LSA	Latent Structure Analysis

1. Introduction

a. Motivation and Problem Statement

Matchmaking is an autonomous process of indexing and matching players based on opportunistic algorithms. Traditionally, players are connected in online games using manual discovery techniques; such as browsing visible games server and inviting known players. Matchmaking system enables unsupervised player discoveries based on some criteria without the needs of any aforementioned a-priori. Matchmaking system evaluates a set of metrics to identify the most optimal matching of some correlated players for improved gaming experience. Some common metrices include in-game skill levels, connectivity parameters and player preferences.

Dota2 use Matchmaking Rating (MMR) and seasonal ranking medal to arrange player on the online play sessions. Each player is given a MMR to represent their skill level. A rank consists of certain range of MMR value. The system will let player with same rank to play together in a game session. Winning increases a player's MMR while on the other hands, losing decrease it.

Currently, Dota2 is using MMR-based and seasonal ranking medal-based matchmaking system to put players with similar skills together in a game. In the context of skills-based matchmaking, player's in-game proficiency is profiled and inferred to match a set of similarly skilled players. Existing methods use game specific attributes for player profiling. Game-specific attributes in existing matchmaking system do not effectively describe player's specific traits that are implicit to effective behavioral based matchmaking algorithm.

By, using skills-based matchmaking algorithm, it is common that most of the team consists of unbalanced team roles. For example, the team may consist of the all core player (carry) without any support player (support). Moreover, player may try to balance the roles in the team by choosing a role that he or she do not excel in. Thus, a player's role-based matchmaking system is used to improve the division of roles in a team from the skills-based matchmaking system. This project identifies and proposes a set of useful attributes using heuristics and machine-learning to effectively quantify player's skillsets in the domain of MOBA games.

b. Background

In the earliest online games, players were required to exchange their IP address in order to play with each other through online. After that, it evolved into more permanent dedicated server addresses that added into the games. Later, ranking system and playlists is used to play an online game session. From that onwards, most of the games adopt this approach and become the most popular method of arranging online games sessions until now.

Many matchmaking systems make use of skill estimates or ranks. The ranking system allows players that have similar skills or abilities to play against each other, giving closer and more competitive games for all skill ranges. One of the examples is the Xbox Live's TrueSkill system.

TEAM 1	MMR	TEAM 2	MMR
Player 1 **(Level 26)**	1750	Player 1 **(Level 27)**	1790
Player 2 **(Level 30)**	1700	Player 2 **(Level 26)**	1710
Player 3 **(Level 29)**	1685	Player 3 **(Level 29)**	1705
Player 4 **(Level 25)**	1720	Player 4 **(Level 27)**	1715
Player 5 **(Level 26)**	1735	Player 5 **(Level 29)**	1700
Max Diff.: 65 **Avg. MMR:** 1718		**Max Diff.:** 90 **Avg. MMR:** 1724	

Figure 1 - MMR-based matchmaking system

Dota2 use MMR-based and seasonal ranking medal matchmaking system to put players into team on the online play sessions. Each player has a MMR value that given by the system after playing a few games. The matchmaking is similar to the Elo system. Players of roughly equal skill will be placed in the same game.

Figure 2 - Seasonal ranking medal

Player's role-based matchmaking system put players into a team based on what roles the player excels in. A profile for each player is created which can identifies the personalities and behaviors of the player. An algorithm is use to determine the what roles is most suitable for the player based on the profiles. Then, the matchmaking system will put players with different roles into a team for gaming sessions.

c. **Objectives**

i. **Synthesize existing matchmaking techniques in terms of the attributes used for player profiling and for subsequent team recommendation**

Existing matchmaking system is study and all the attributes used in the system is examined clearly. The existing matchmaking system is also being reviewed on how it chooses player to put into a team.

ii. **Identify a set of metrics to measure individual human personalities to be used as features for matchmaking algorithm**

A list of metrics that can describe human personalities is generated. Every metrics is considered carefully to get the best attributes use to create player's profile for each player.

iii. **Design feature extraction algorithms based on self-defined feature set to automate dataset collection**

An algorithm is created using data mining technique to extract needed data that fits the feature which is decided. The algorithm will form a unique profile for every player with the data collected. The profile is used for the matchmaking system to put players in a team.

iv. **Optimize behavioral-based matchmaking algorithms using player traits' features in team recommendation**

A scheduling and optimization algorithm are created to satisfy the purpose for choosing the most appropriate player to form a balance team. The algorithm will search all players that queuing for a match and view the player's profile, then matches the appropriate players into a team. The algorithm also created with the conditions of the team should be a balance team that each player have their own roles. The algorithm also uses some sliding window mechanism so that players would not be waiting in a queue for a long time.

d. Proposed Approach

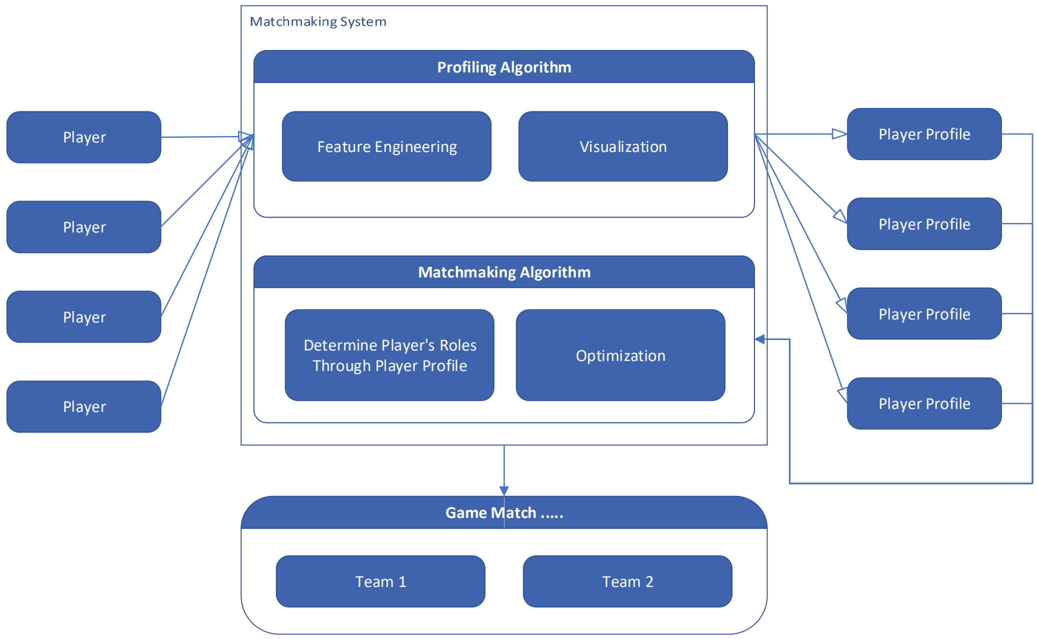

Figure 3 - System Design

The figure above show that the design of the proposed matchmaking system. The matchmaking system is classified into traits-based matchmaking system which use the behavior of the players in the game to match them together in teams in gamming sessions.

When players join a gamming session, the system put players into a pool of players. The matchmaking system consists of profiling algorithm and matchmaking algorithm. The profiling algorithm will take player's previous data to create player's profile. Then, the matchmaking algorithm will take players from the pool and put them into teams according to the player's profile.

e. Work Has Been Achieved

The player data needed for the matchmaking system to create player's profile is collected by using the Dota2 API and Dotabuff.com. The data get from the Dota2 API and Dotabuff.com is cleaned and restructured for easier data extraction. Text mining, data normalization and natural language processing techniques are used when collecting the data from Dota2 API and Dotabuff.com.

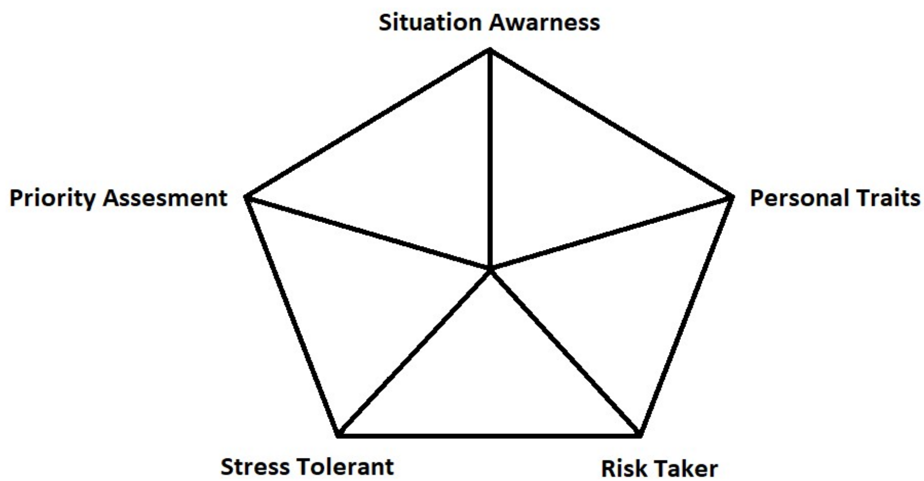

Figure 4 - Proposed player's profile

Analysis is done on the data collected to determine the most appropriated attributed needed to create unique player's profile. The general-based attributed that determined due to heuristic for the player's profile based on the behaviors of the players are situation awareness, priority assessment, personal traits (friendliness, toxic level, team leadership), stress tolerant and risk taker.

Situation awareness is to determine how well the player aware of what is happening around his avatar and react to the events happening. Priority assessment is to determine how often the player aim for the objectives in the gamming sessions. Personal traits is use to measure how the players communicate with other players in the gamming sessions. Stress tolerant is determine by how the players performed in the gamming sessions when under pressure. Risk taker is used to measure how much risk will the player take to achieve advantages in the gamming sessions.

f. Report Organization

Chapter 1: Introduction

The current matchmaking system of Dota2 is skill-based matchmaking system that use player's skill to put players into team. The players always encounter unbalanced teams in the gamming sessions by using skills-based matchmaking system.

Chapter 2: Literature Review

A few case studies have been reviewed to learn what behaviors of the players in the gamming sessions are studied and how the player's behaviors have affected the gamming environment of the players in a gamming session.

Chapter 3: System Design

The existing skills-based matchmaking system are reviewed and studied to understand the benefits and weaknesses for the players in the gamming sessions. A set of metrics that can use to describe player's behaviors in gamming sessions are identified. The profiling algorithm will create unique profile for each player based on the metrics decided. The matchmaking algorithm will then use the profile created to put players into team for gamming sessions. The effectiveness of the matchmaking system is evaluated by using a universal evaluation system.

Chapter 4: Methodology and Tools

Some techniques and tools are used to create the player's traits-based matchmaking system. The techniques and tools used include machine learning, text mining, data normalization, natural language processing, visualization, correlation feature selection, scheduling and optimization.

Chapter 5: Results

The player's traits-based matchmaking system is evaluated by using the feedback of the players after playing in the gamming sessions using the matches created by the matchmaking system. From the results, the players have a more enjoyable and comfortable gamming sessions by using the matches created by the player's traits-based matchmaking system compared to the skills-based matchmaking system.

Chapter 6: Conclusion

From the player's feedback, it is proved that the player's traits-based matchmaking system can provide better gamming experience for the player than the original skills-based matchmaking system. However, there are also a few matches created by the traits-based matchmaking system did not meet the expectation of the players. Thus, improvement of the traits-based matchmaking system may be done in the future by adding more attributes into profiling algorithm and let the matchmaking system support in games with languages other than English.

2. Literature Review

a. A Survey and Analysis of Techniques for Player Behavior Prediction in MMORPGs

Harrison, B., Ware, S., Fendt, M. and Roberts, D. (2014) done research of player modelling in massively multiplayer online role-playing games (MMORPGs). Three classes of player modelling techniques which is manual tagging, collaborative filtering and goal recognition was surveyed and evaluated. Desiderata is use to list out the strength and weaknesses of each techniques in an MMORPG. A model-based collaborative filtering algorithm is used to predict the achievement in the MMORPG. Desiderata is use to analyse the result and evaluate the techniques used for the MMORPG. These is used to improve the experience of the players in MMORPG.

	$t = 0.6$		$t = 0.7$		$t = 0.8$	
	Precision	Recall	Precision	Recall	Precision	Recall
Clique	0.73 ± 0.14	0.46 ± 0.09	0.76 ± 0.12	0.42 ± 0.10	0.80 ± 0.14	0.36 ± 0.08
Random	0.20 ± 0.11	0.11 ± 0.03	0.21 ± 0.11	0.10 ± 0.03	0.20 ± 0.11	0.08 ± 0.02
Significance	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p < 0.05$

Table 1 - Summary of results of clique-based models against models created by a random baseline

The performance of the clique-based models against the random baseline models is compared and shown in the table above.

Technique	Scalability	New Data	Authorial Burden	Unsupervised Performance	Noise Tolerance	Accuracy
Manual Tagging	●	○	○	○	○	◐
Memory-Based CF	○	●	●	●	◐	●
Model-Based CF	●	◐	●	●	◐	●
Planning-Based Goal Recognition	○	◐	○	●	○	◐
Probabilistic Goal Recognition	●	◐	◐	◐	●	●

Table 2 - Summary of technique performance on the desiderata

Many popular techniques for player modeling have been evaluated and the effectiveness of each techniques is measured and evaluated. The results of the techniques used in MMORPG is shown on the table above. This result show that game designers can use desiderata to evaluate the effectiveness of player modeling techniques in the MMORPG.

b. Behavioral Profiles of Character Types in EverQuest II

Shim, K.J. and Srivastava, J. (2010) study the behavioral profiles of different character types in EverQuestII which is a popular MMORPG developed by Sony Online Entertainment. The player's game data is used to construct the behavioral profiles of the players use for normal behavior recognition and detect anomalies. The behavioral profile can show what the play does to level up and how they precede the quest for level up. The profile also shows how the player work with other player to do a quest. A few frameworks are proposed to do the automatic behavior profiling which is segmentation analysis of historical player behaviors, behavior profiling of input users and recommendation of tasks based on input user's objectives.

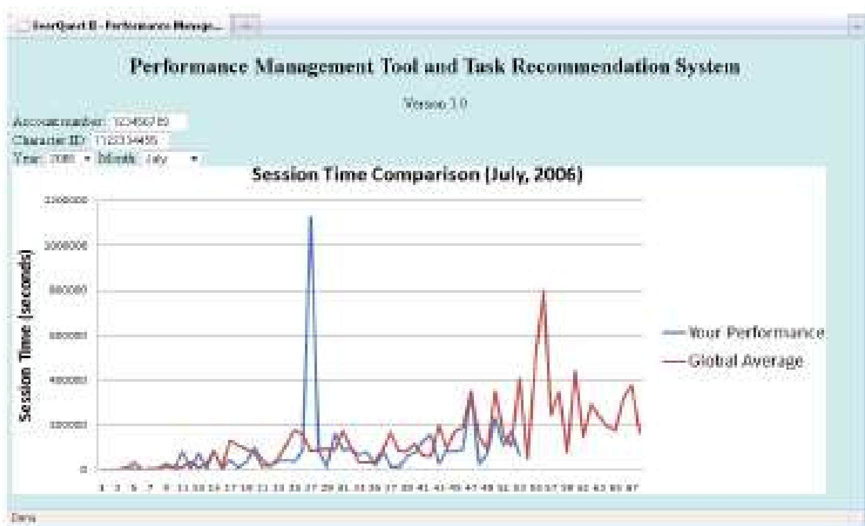

Figure 5 - Performance Management Tool and Task Recommendation System

According to Shim, K.J. and Srivastava, J. (2010), The Player efficiency which is a function of the total XP gained is examined using the performance management tool and task recommendation system on EverQuestII. Then, the player busyness is examined across all sub-classes in the game. After that, the ratios of group activities versus solo activities of the players are examined. By study the information collected, it is expected the behavioral profile is a valuable addition to the EverQuestII.

c. Comparative Cluster Analysis and Behavioral Profiling in Destiny

Drachen, A. et al. (2017) develop behavioral profiles for the online multiplayer shooter/role-playing game which is called Destiny. The profiles contain 41 playstyles features and over 4800 randomly selected players from the Destiny. Four types of clustering techniques are used for the Destiny which is the k-means, gaussian mixture models, k-maxoids and archetype analysis. The models are used for two type of game modes in Destiny, the PVP and PVE. Cross-model analysis is used to identify four to five distinct playstyles from each method by similarity metrics.

		Gaussian Mixture Models			K-Means Clustering			K-Maxoids			Archetype Analysis		
		4 Clusters	5 Clusters	6 Clusters	4 Clusters	5 Clusters	6 Clusters	4 Clusters	5 Clusters	6 Clusters	4 Clusters	5 Clusters	6 Clusters
Gaussian Mixture Models	4 Clusters	1	0.6	0.6	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1
	5 Clusters	0.2	1	0.7	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1
	6 Clusters	0.4	0.3	1	0.2	0.2	0.2	0.0	0.1	0.1	0.1	0.1	0.1
K-Means Clustering	4 Clusters	0.1	0.2	0.2	1	0.6	0.5	0.1	0.2	0.2	0.3	0.3	0.3
	5 Clusters	0.1	0.2	0.2	0.6	1	0.8	0.1	0.1	0.3	0.3	0.4	0.3
	6 Clusters	0.1	0.2	0.2	0.3	0.5	1	0.1	0.1	0.3	0.3	0.4	0.4
K-Maxoids	4 Clusters	0.1	0.1	0.1	0.1	0.1	0.1	1	0.6	0.2	0.1	0.1	0.1
	5 Clusters	0.1	0.1	0.1	0.2	0.2	0.2	0.2	1	0.2	0.1	0.1	0.1
	6 Clusters	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.6	1	0.2	0.3	0.2
Archetype Analysis	4 Clusters	0.1	0.1	0.1	0.5	0.5	0.3	0.1	0.3	0.3	1	0.3	0.3
	5 Clusters	0.1	0.2	0.2	0.4	0.4	0.4	0.2	0.3	0.3	0.4	1	0.3
	6 Clusters	0.1	0.1	0.1	0.3	0.3	0.3	0.1	0.2	0.2	0.4	0.2	1

PvE Similarities

PvP Similarities

Figure 6 - Adjusted Mutual Information for Various Clustering Results

According to Drachen, A. et al. (2017), the patterns in the behavior of the players were highlighted in the game across the PVP and PVE modes in Destiny. The performance and playstyles of the players are measures using the behavioral profile pattern. Future, a recommender system which will suggest the most useful items to the players can be develop in Destiny.

d. Detecting Predatory Behavior in Game Chats

Cheong. Y.G. et al. (2015) studies how to detect predatory behavior in the chat of a MMO game for children which is MovieStarPlanet. Using machine learning method, the system is aim to detect the predatory behaviors in the chats. Extensive preprocessing is used to increase the accuracy of the system in detecting predatory behaviors. The performance of the three different strategies for data selection and pre-processing are compared and analyzed.

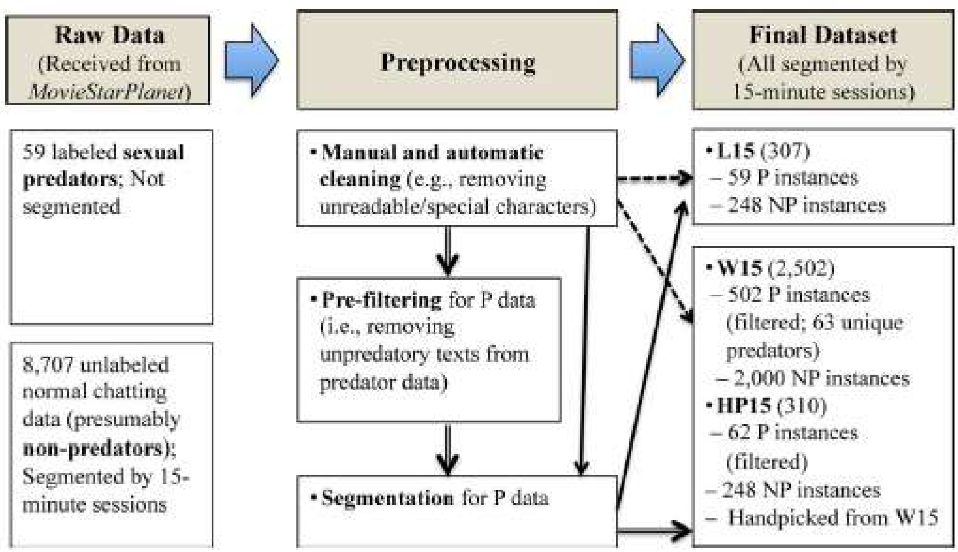

Figure 7 - Overview of the data preparation process and final data subsets after pre-processing

Three type of preprocessing strategies which is bag of words, sentiment features and rule-breaking features are use to detect the sexual predators using the real chart data from MovieStarPlanet. Bag of word is useful to detect predatory behavior when the chat contains predatory words. The sentiment features are useful when combine with the bag of word to detect predatory behaviors in processing big data. The behavior features are useful when the data contains less predatory languages.

e. Sequence Alignment Based Analysis of Player Behavior in MMORPGs

Shim, K.J. and Srivastava, J. (2010) want to develop a sequence alignment-based behavior analysis framework (SABAF) for EverQuestII. The sequence alignment-based behavior analysis framework is used to predict the inactive players in EverQuestII is either stop playing the game for a long period of time or leave the game permanently. It is aim to show that data analysis methods can successful applied in inactivity prediction of players in EverQuestII.

Global and local sequence alignment algorithm is used with a unique soring scheme in SABAF to measure the similarity between activity sequences. There are three components in SABAF which is sequence alignment-based customer profile database, feature selection schemes and prediction model building, and decision support model. These components are used to determine the inactive players in EverQuestII. From the result, SABAF feature selection schemes successful produce the prediction coverage of the inactive player in EverQuestII.

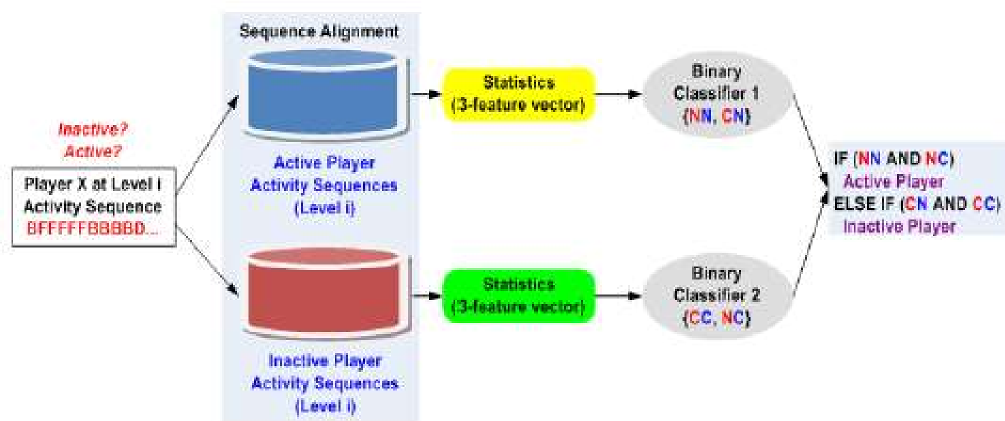

Figure 8 - SABAF Workflow

f. The Clusters of Gaming Behavior in MMORPGs

According to Wang, S.T., Yang, J.C., Chen, S.Y. and Kuo, W.C. (2012), online gaming behavior and special underlying social group structures are determined to have relationship with each other by using the player information in MMORPG. It is investigated whether that different avatars will affect the player gaming behaviors. Six-cluster model are use for determine the effect of different avatars on the gaming behaviors.

Indicators		C1	C2	C3	C4	C5	C6	Wald	P	R2
Cluster Size		0.314	0.24	0.14	0.132	0.113	0.063			
Instance		-0.77	-2.89	0.41	3.574	1.049	-1.39	342.74	0.00	0.70
Buy		-1.70	-2.29	1.21	3.480	-0.79	0.09	243.14	0.00	0.67
Shop		-0.40	-1.42	-0.04	1.440	0.73	-0.31	349.44	0.00	0.47
Quest		-0.31	-2.84	0.52	4.066	2.48	-3.91	245.45	0.00	0.76
Sell		-1.31	-1.88	0.96	2.846	-0.57	-0.04	322.94	0.00	0.60
Player Gender		-0.06	0.00	0.24	-0.062	-0.296	0.174	16.710	0.01	
Avatar Gender		0.04	0.07	0.03	0.145	0.173	-0.454	19.817	0.00	
Occupation Types	Defender	-0.10	-0.04	0.07	-0.10	-0.01	0.18	21.85	0.02	
	Gunner	-0.09	-0.03	-0.23	0.15	-0.17	0.37			
	Mage	0.19	0.07	0.16	-0.05	0.18	-0.55			

Table 3 - The parameters of 6-Cluster Model

Gaming behavior, player gender, avatar gender and avatar occupation types are use for analysis. The latent class analysis is used to determine that if different avatars affects the gaming behaviors. The gaming behaviors are divided into six groups. Each group representing a different types of gaming behaviors. From the result, the gaming behavior can be predicted based on the player gender, avatar gender and occupations types.

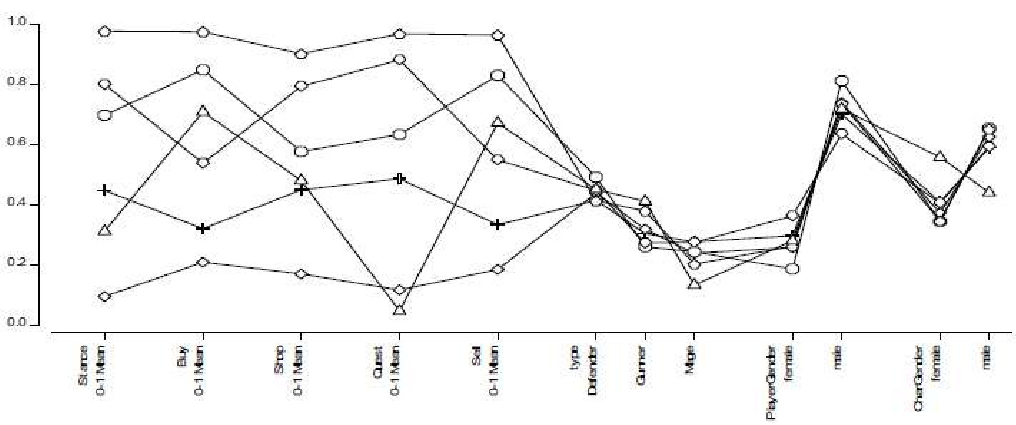

Figure 9 - The six clusters distribution of five types of gaming behaviors and player gender, avatar gender and occupation types

g. The Identification of Ability Profiles for Different Roles in an Online Multiplayer Video Game in Order to Improve the Overall Quality of the New Player Experience

Koles, M. and Peter, Z. (2017) proposed to develop a system to help new player to have a good experience in playing the game and help to decrease the toxic behavior in the game which is called League of Legend (LOL). By using ability profile, customized tutorial sessions and recommendations are given to the new players to familiarize the game. This will improve the first impression of the game to new players. Koles believe that the toxic behavior on new player in the game can be reduce by have better performance.

According to Koles, M. and Peter, Z. (2017), the tutorials are use to teach new players the game basic and the overall idea of how the game is played. The tutorial should try to estimate what the skill of the player in the game and create customized tutorial for the player to increase the player's skills. The system also can recommended what characters roles of the game that the player are excels in based on the estimated playstyles of the new players.

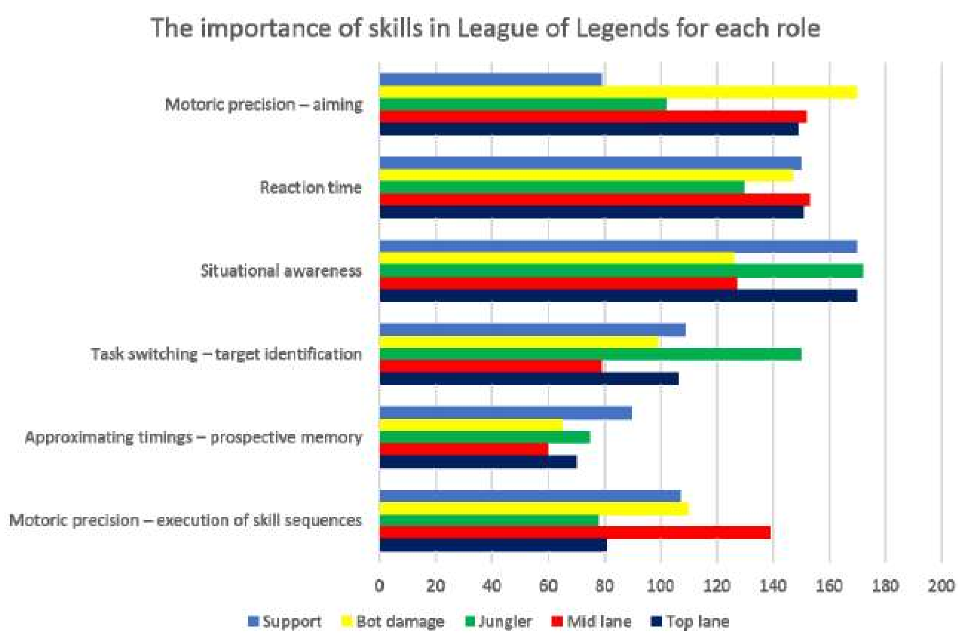

Figure 10 - The importance of the six skills by roles, identified by the focus groups. Higher numbers mean higher priority

h. The Social Behaviors of Experts in MMORPGs

Huffaker, D. et al. (2009), studies how the behaviors of the experts in the game called EverQuestII. Exponential Random Graph Models (ERGM) are used to examine the social network of the players in the game.

Variable	Estimate	Std. Error	GOF
Directed chat	–8.281***	.0438	.92
Mutual chat	8.609***	.0849	.96
Expert-initiated chat	.002***	.0003	.54
Expert-targeted chat	.002***	.0003	.22
Expert-targeted chat (level)	.004***	.0002	.50
Chat based on expertise difference	–.002***	.0001	.44
Degeneracy value	.096		

Note: ***p<.001.

Table 4 - Summary of ERGM results for achievement models of game expertise

Variable	Estimate	Std. Error	GOF
Directed chat	–8.185***	.0510	.82
Mutual chat	8.641***	.0862	.80
Expert-initiated chat	.0000	.0002	.56
Expert-targeted chat	.0002	.0002	.76
Expert-targeted chat (level)	.0045***	.0002	.26
Chat based on expertise difference	–.0005***	.0001	.86
Degeneracy value	1.08		

Note: ***p<.001.

Table 5 - Summary of ERGM results for performance models of game expertise

According to Huffaker,D. et al. (2009), found out that who perform more communication than others achieve more in the game than other players that did not communicate in the game. Besides, the result show that the achievement and performance experts tend to communicate with other players that have similar or higher expertise. The high-level experts are also most likely to receive communication from others players.

i. The Study of Adolescent Behavior in Playing Online Games

Harnadi, B. (2017) investigate the relationships between the adoption of online games technologies among adolescences and the behavior of the players when playing the games. A few variables which is perceived enjoyment, flow experience, performace expectancy, effort expectancy, social influence and facilitating conditions are used in the models to analyze the relationships between the players and their behavior while playing the online games.

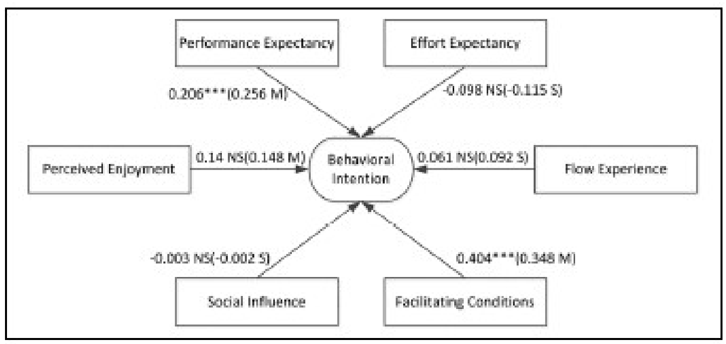

Figure 11 - The Result of Analysis of Theoretical Model

From the study, Harnadi, B. (2017) found out that education and age did not have sufficient correlation ship with the experience and the time spent by the players on playing online games. The results also show that the spent of time in playing online games had significant positive correlation to all variables except the social influence of the players. This means the longer the players play the online games, the players will find more enjoyable, string belief and easier to use the game system when playing the online games.

j. Traffic and User Behavior Analysis of Online Mobile Game

Xiong, Y., Liu, J., Lei, Z. and Chen, L. (2015) analyses the user behavior of the mobile games by extracting information of the online mobile game from the traffic records. Distributed computing platforms which consists of Hadoop Distributed File System (HDFS) and MapReduce are used to analyze the information collected from the mobile games. Activeness, diurnal variation, account distribution and version distribution are used as attributes to analyze the user behavior of the mobile games.

Xiong, Y., Liu, J., Lei, Z. and Chen, L. (2015) found out that the subscribers of the network providers tend to play online mobile game after work. The results also show that most users only have one accounts in the mobile games. Furthermore, competitions between the is quite fierce can be indicate by the well-distributed account distribution. The results also show that most of the users use the latest two version among so many versions.

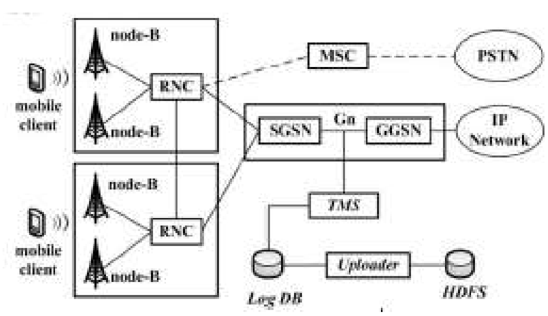

Figure 12 - Cellular network with data capture devices

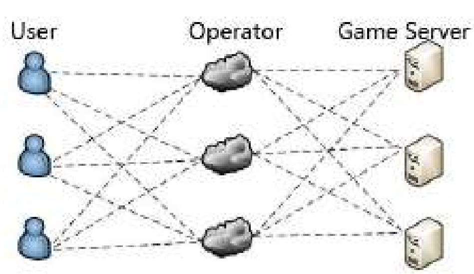

Figure 13 - Communication Topology

k. Use Behavior Modeling Approach for Churn Prediction in Online Games

Borbora, Z.H. and Srivastava, J. (2012) propose that to use churn prediction models and lifecycle-based approach to classified the player more accurate based on the player behaviors from the captured logs. The churn prediction models is use to analyze the activity traits of churners until the termination point and compare the activity traits with the regular players. Distance-based classification which called wClusterDist is used to compare the distinct behavioral profiles between churners and active players.

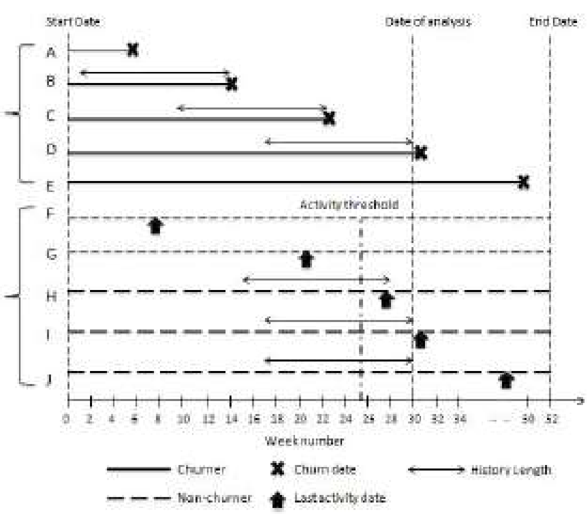

Figure 14 - Different player lifecycle scenarios

From the analysis, Borbora, Z.H. and Srivastava, J. (2012) state that by using churn predictive models, it has good predictive power. The churn predictive models also provide insight on how the churn behaviors in the MMORPG. Moreover, it can use to identify the distinct behavior between the churners and active players based on the behavioral profile created. The results show that the churn predictive models is a well-suited classification method which has performance better than other traditional classifiers.

3. System Design

a. Overview

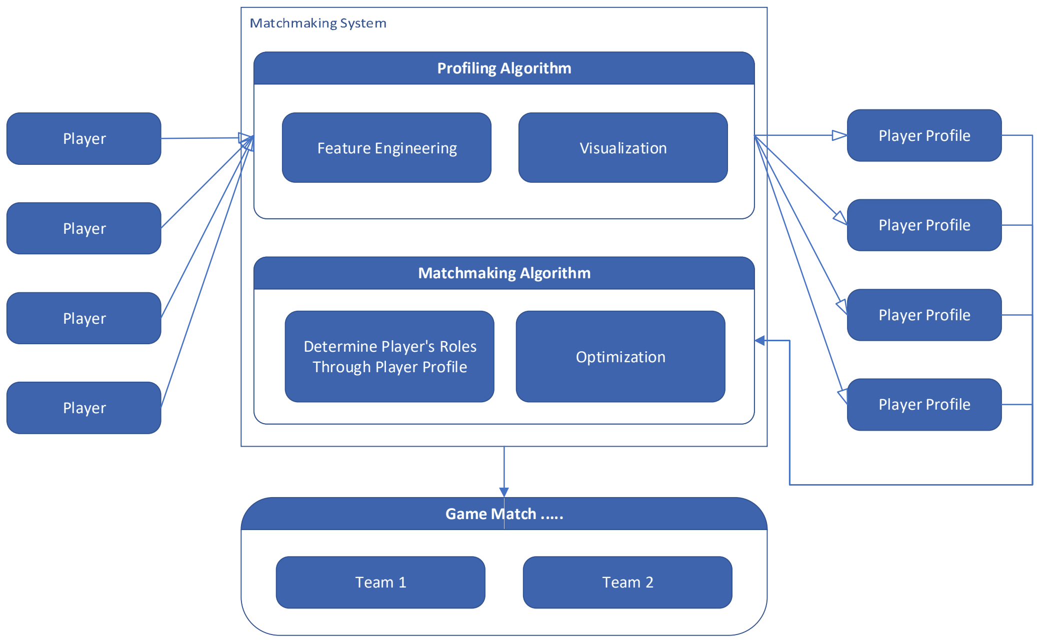

Figure 15 - System design overview

Figure 15 show that the system design for the traits-based matchmaking system. When players join a gamming session, the system put players into a pool of players. The matchmaking system consists of profiling algorithm and matchmaking algorithm. The profiling algorithm will take player's previous match data to create unique player's profile. Then, the matchmaking algorithm will take players from the pool and put them into teams according to the player's profile.

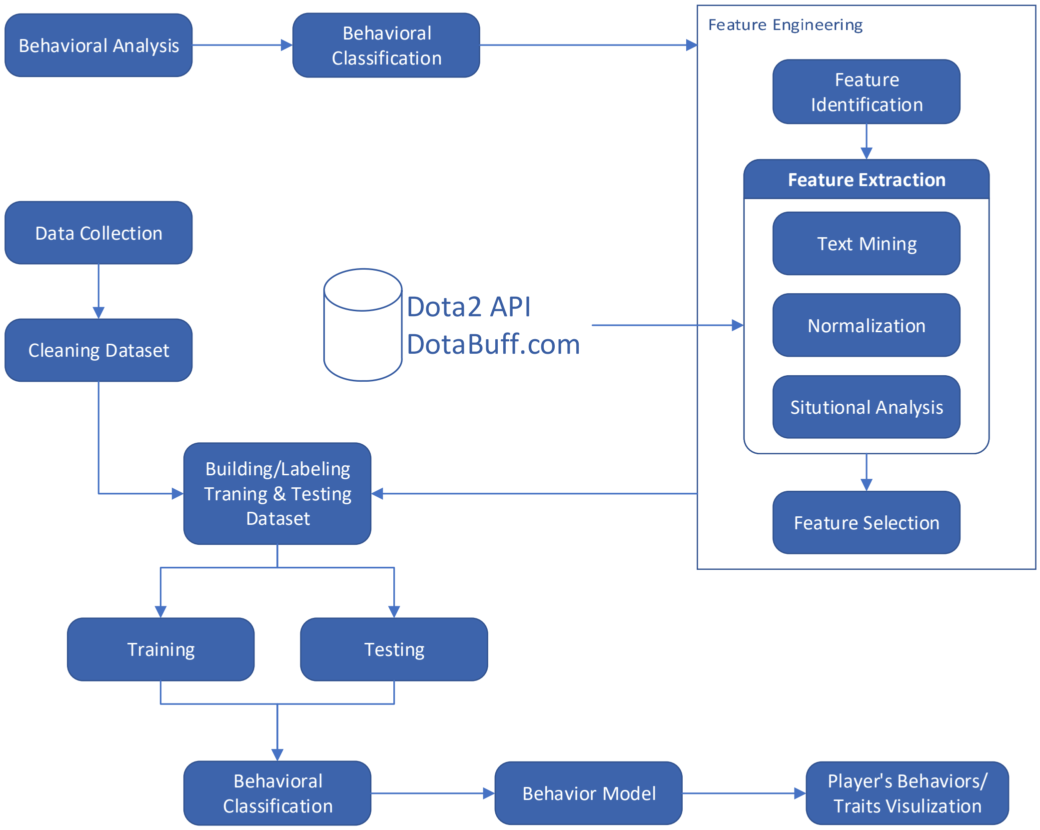

Figure 16 - System design detail

Traits-based matchmaking system use player's game behavior to create profiles for them. The behavior of the players is observed and identify. Then, the player's behavior is analyses through behavioral analysis. This show what and how the player's behavior has impact on the gamming sessions.

Using information from the behavior analysis, player's behavior is divided into different classes. All the player's behavior is classified into different classes so that it is easier for feature engineering to get the best feature for the profiling algorithm. With the behavior of the player classified, the behavior that can differentiate between different types of player can be identified and how these player's behavior can affect the gamming sessions.

Feature engineering is use to create and provide features for the profiling algorithm to work using the domain knowledge of the data. In feature engineering, there are feature identification, feature extraction and feature selection. In feature identification, the information from behavioral classification is used to identify which player's behavior is the most effective in describing a player's traits for the profiling algorithm.

In feature extraction, all features of data in Dota2 API and Dotabuff.com is extract and classify. The features get is normalized and restricted. Analysis is then done to the data to show what and how the features work for the profiling algorithm. In feature selection, the features that is most effective for the profiling algorithm is used according to the analysis performed on the features get.

In data collection, the data is got by using the Dota2 API and Dotabuff.com that can provide all the data needed. Text mining is used to get data from Dota2 API and Dotabuff.com in JSON format. The data is then clean for the profiling algorithm to use. Normalization is used on the data to get rid of duplicate or not useful data and restructuring the data so that getting the data needed is easier. The cleaned data is divided into training set and testing set according to 7:3 portion. The dataset is then built and labeled for training set and testing set.

The profiling algorithm use the training dataset to train and build the behavior model for the player's profile. Then, the profiling algorithm will use the testing data to create the behavior model for the player. The player's behaviors and traits is then visualized through player's profile.

Figure 17 - Profile visualization

Figure 17 show that the player's profile that will show the player's behavior in the gamming sessions. It consists of five of the player's behavior in the gamming sessions which is situation awareness, priority assessment, personal traits, stress tolerant and risk taker.

Situation awareness is the perception of the surroundings and events around the player's character. Situation awareness measures how well the player aware of what is happening around him and react to the events happening. Priority assessment is stating what is the main goals and what is the minor goals in the gamming sessions. Priority assessment measures how often the player aim for the objectives in the gamming sessions.

Personal traits that consists of friendly, toxic and team play attributes are the personality behavior of the players in the gaming sessions. Personal traits measure how the players communicate to other players. Stress tolerant is how the player act in the gamming sessions when under pressure. Stress tolerant measures how the players playing in a gaming session when facing different types of opponents. Lastly, risk taker is measure through players taking risk to take advantage in the gamming sessions.

Each attribute in the player's profile is divide into ten segments which is range from 0.0 to 0.9 to show how rating of the player's behavior in each attribute. Below is the list of how the player's behavior rated in each attribute:

<u>Situation Awareness</u>

0.0: change 0 item in 100% of the game

0.1: change 1 item in 30% of the game

0.2: change 2 items in 40% of the game

0.3: change 3 items in 40% of the game

0.4: change 3 items in 50% of the game

0.5: change 4 items in 50% of the game

0.6: change 4 items in 60% of the game

0.7: change 5 items in 60% of the game

0.8: change 5 items in 70% of the game

0.9: change 6 items in 70% of the game

<u>Priority Assessment</u>

0.0: 0 objectives destroy

0.1: 1 objectives destroy

0.2: 2 objectives destroy

0.3: 3 objectives destroy

0.4: 4 objectives destroy

0.5: 5 objectives destroy

0.6: 6 objectives destroy

0.7: 7 objectives destroy

0.8: 8 objectives destroy

0.9: 9 objectives destroy

Personal Traits

0.0: 0% of the word is friendly/toxic/team play

0.1: 1% to 10% of the word is friendly/toxic/team play

0.2: 11% to 20% of the word is friendly/toxic/team play

0.3: 21% to 30% of the word is friendly/toxic/team play

0.4: 31% to 40% of the word is friendly/toxic/team play

0.5: 41% to 50% of the word is friendly/toxic/team play

0.6: 51% to 60% of the word is friendly/toxic/team play

0.7: 61% to 70% of the word is friendly/toxic/team play

0.8: 71% to 80% of the word is friendly/toxic/team play

0.9: 81% to 90% of the word is friendly/toxic/team play

0.9: 91% to 100% of the word is friendly/toxic/team play

Stress Tolerant

0.0: 0% time perform unwell with high ranking players

0.1: 10% time perform unwell with high ranking players

0.2: 20% time perform unwell with high ranking players

0.3: 30% time perform unwell with high ranking players

0.4: 40% time perform unwell with high ranking players

0.5: 50% time perform unwell with high ranking players

0.6: 60% time perform unwell with high ranking players

0.7: 70% time perform unwell with high ranking players

0.8: 80% time perform unwell with high ranking players

0.9: 90% time perform unwell with high ranking players

<u>Risk Taker</u>

0.0: 0% time take unfamiliar hero to counter opponent hero

0.1: 10% time take unfamiliar hero to counter opponent hero

0.2: 20% time take unfamiliar hero to counter opponent hero

0.3: 30% time take unfamiliar hero to counter opponent hero

0.4: 40% time take unfamiliar hero to counter opponent hero

0.5: 50% time take unfamiliar hero to counter opponent hero

0.6: 60% time take unfamiliar hero to counter opponent hero

0.7: 70% time take unfamiliar hero to counter opponent hero

0.8: 80% time take unfamiliar hero to counter opponent hero

0.9: 90% time take unfamiliar hero to counter opponent hero

b. Implementation Issues and Challenges

There are a few limitations founded in this project. Because of the limited time to complete this project, the matchmaking system that is created may not produce the ideal result from the simulation. Below are the limitations for the proposed matchmaking system:

Game Chat (Locale)

The player profiling algorithm only use text data in English for text-analysis. The proposed text mining algorithm does not recognize any other language like Chinese, Thai or German language. Since, the input to the profiling is derived from in-game engine, the matchmaking system only works for the English version of the game client.

Number of Attributes

The optimal number of attributes and the attributes themselves are determine based on heuristics due to lack of baseline for this parameter. Adding more attributes may potentially improve the results, however this is beyond the scope of this project. Besides, the player profile is non-real time and not automatically adaptive with player's skillset growth. Player profiles need to be refreshed periodically with new set of training data.

4. Discussions

a. Methodology

The current Dota2 matchmaking system is a skills-based matchmaking system which pair up players with equal skill level into a team. First, the Dota2 MMR and seasonal ranking medal system is being reviewed thoroughly.

The attributes used for player profiling and for subsequence team recommendation is examined and understand. The attributes used can be replaced by more advance metrics that can determine individual human personalities. A list of metrics that describe the human behaviors traits is created and used for player profiling.

A feature extraction algorithm is design to get dataset collection from text file through data mining with the self-defined feature set automatically. Player's profile is created based on the data collected. The player's profile then is used for the optimized behavior-based matchmaking algorithm using player trait's features in team recommendations.

A universal evaluation system for matchmaking designed to evaluated the effectiveness of traits-based matchmaking system using match reports statistical analysis. The result is compared to the skills-based matchmaking system to show that traits-based matchmaking system is more effective than the skills-based matchmaking system.

b. Techniques Used

In order to create the traits-based matchmaking system, some tools and methods are used in creating the proposed system. Below is the list of tools and methods used:

Machine Learning

Machine learning is start from pattern recognition and the theory that the computers can learn by themselves without being programmed to do any specific tasks. It focuses on the development of the programs that can access to data and use it to learn and improve the solution.

Machine learning is use in the matchmaking system to train the algorithm to know how to pick the appropriate players to form a team from a pool of queuing players. With machine learning, the system will be trained with training data first. The system will improve with more data feeding to the system. Them, the matchmaking system can perform more better in selecting the right players to form a team.

Text Mining/Data Normalization/Natural Language Processing

Text mining which is also called text analytics is the process of deriving useful information from a text. The useful information is usually obtained through determining patterns and trends in the texts with the assistance of statistical pattern learning. IT is used to turn text into data for analysis by applying analytical methods and natural language processing.

Data normalization is a process that the data attributes in a data model are organized to increase the cohesion of entity types. It is used to reduce or remove data redundancy. This make the database easier to maintains its information.

Natural language processing is concerned about the interactions between computers and human languages. It understands, analyze and generate language he is use by humans instead of computer languages.

The matchmaking system also using text mining, data normalization and natural processing to work perfectly. The data of the players is collected and data normalization is performed on the data required. Then, the data is read by the system by using text mining technique to get useful data from it. It also uses natural language processing technique to perform the data analysis.

Visualization/Profiling

Visualization is a method that turn some useful information into somethings that can be seen. Profiling is a method that collect and analysis information about a person characteristics or behavior patterns in order to describe a person.

Every data of the players in the game is collect by the system and use to create profile for each player with specific attributes or descriptions. The information of a player is visualized through the profile so that people can understand it. The profile of a player shows all useful information to others so that everybody can understand what the player behaviors in the game.

Correlational Feature Selection

Feature selection is also called variable selection, attribute selection or variable subset selections. It is a process of selection of attributes in the data for the use of predicting modeling problem or model constructing. The correlational feature selection is an algorithm that evaluates subsets of features with an appropriate correlational measure and a heuristic search strategy.

This method is used to generate and construct useful models from data get from data mining. This is because it simplifies the models to make it easier to interpret by users and enhanced the generalization by reducing overfitting. It can also avoid the curse of dimensionality for the construction of models. Then, the wrapper models are used to train the matchmaking system by using machine learning.

Scheduling/Optimization (Context Aware)

Scheduling is a process that specified how to assign the resources among the system to complete the work. A scheduler is what will carry out the scheduling process. It is used to distribute the resources of the system evenly so the work can be done more efficiently. It aims to maximize throughput and fairness, minimizing respond time and the latency of the system.

Optimization is the process of modifying a system so that it can work more efficiently and use fewer resources by adding some features on the system. By using optimization on the system, it can work more faster and with less resources requirements or consume less energy.

The player's role-based matchmaking system use scheduling so that it can get the resources to run the systems. By using optimization, the algorithm or the matchmaking system was refined to work more efficiently and use less resources.

c. Pseudocodes

```
Function get player (player id)
    Set the API to Dota2 API
    Get the status from the API
    If the status code is 200
        Get player detail from API
        Get player word history from API
        Get player match detail from API
        Get player ranking/rating from API
        Return the information get from API
    Else
        Print “Dota2 API is down” message
        Exit function
    End If
End Function
```

The pseudocodes above is a function to get the information and data needed from the Dota2 API to create unique profile for each player. The function will be connected to the Dota2 API and verify the status of the Dota2 API. If the Dota2 API is functioning, the function will get the player details, history matches details, chat history and the rating or ranking of the player. Then, the function will return all information collected as an object for other functions to create the unique player’s profile. If the status of the Dota2 API is not good, the function will show that the Dota2 API is down and not usable, then exit the function.

Function profile visualization (player id)

Find player details from the player list that has the player id

Set the label of the profile

Set the range of the profile

Set the player id as the profile title

Set the point on the profile based on the player details

Plot the points on the profile

Display the profile

End Function

The pseudocode above is a function to visualize the player's profile created for the player and others profile to see. The function will search the player in the player list that contain all the player detail of each player. Then, the function will set the label of the player profile to show the players what attributes is used in creating the player's profile. The function then set the range of each attribute in the player's profile so that the players can understand what their score in certain attributes. The function will also show the player's ID as the title of the player's profile so that everyone will know the profile belongs to which player. The function will set the points on the player's profile based on the data get from the player details. After that, the function will plot the player's profile and visualize it so that the players can see the player's profile.

Function recommendation system (a pool of player)

Calculate the score for each player

Loop until all combination of random 5 players complete

Calculate average score

Find the highest average score

Return the 5-player id that in the group

End Function

The pseudocode above is a function that classify the players into teams based on the player's profile. The function will calculate a score for each player based on the player's profile created. A random of 5 players is group together as a team. Then, the function will calculate the average score of the team and record it. The function will loop until all possible combinations of 5 players as a group done. The average score of each possible combinations of players also being recorded. The highest average score is then determined. The players in the groups with highest average scores are pop out from the pool of players and put into the gamming sessions.

5. Results

There are many types of ways to evaluate the traits-based matchmaking system to prove that is perform more better than the skill-based matchmaking for the player's experience in the gamming sessions. The simplest way to evaluate the matchmaking system is create the teams for the gamming sessions using the traits-based matchmaking system and let the player play the game. Then, the players will rate the matchmaking after playing in the gamming sessions using the teams created.

100 matches have been set up using the traits-based matchmaking system and the players use the teams created to play in the gamming sessions. The players then give a rating from one star to five stars to show if they satisfy with the matches created by the matchmaking system.

The rating given by the players have five level which is:

1 ☆: Worse than the skills-based matchmaking system

2 ☆: Slightly worse than the skill-based matchmaking system

3 ☆: Same as the skills-based matchmaking system

4 ☆: Slightly better than the skills-based matchmaking system

5 ☆: Better than the skills-based matchmaking system

Game No.	Rating
1	5
2	4
3	3
4	5
5	3
6	4
7	3
8	3
9	4
10	2
11	5
12	1
13	5
14	5
15	3
16	2
17	1
18	2
19	2
20	3
21	4
22	5
23	3
24	4
25	4
26	5
27	5
28	4
29	5
30	2
31	1
32	3
33	3
34	1
35	4
36	5
37	3
38	3
39	3
40	4

Game No.	Rating
41	3
42	3
43	1
44	1
45	5
46	3
47	4
48	4
49	3
50	3
51	5
52	4
53	4
54	3
55	3
56	4
57	4
58	5
59	3
60	3
61	4
62	4
63	4
64	3
65	4
66	2
67	5
68	1
69	3
70	3
71	3
72	3
73	4
74	5
75	2
76	4
77	1
78	2
79	2
80	4

Game No.	Rating
81	4
82	2
83	4
84	3
85	5
86	4
87	3
88	2
89	3
90	2
91	4
92	3
93	1
94	5
95	4
96	3
97	5
98	4
99	3
100	3

Table 6 - User Review on Matchmaking System

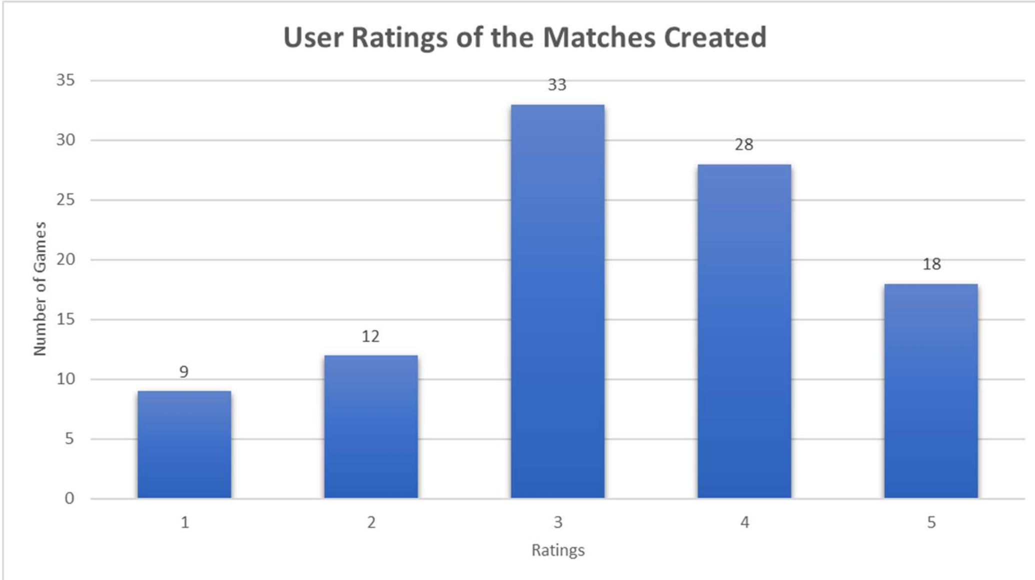

Figure 18 - User Ratings of the Matches Created

The graphs above show that the user ratings of the matches created by the traits-based matchmaking system after the players play in the gamming sessions. From the graphs above, it can find out that the players are quite comfortable while playing in the gamming sessions using the teams created using traits-based matchmaking system.

From the graphs above, players feel that most of the games which consists of 33% of the games created is same as the games created by the skills-based matchmaking system. The players feel that the 46% of the matches created which consists of four stars and five stars ratings are better than the skills-based matchmaking. On the other hand, the players fell that only 21% of the matched created which consists of one star and two stars ratings are worse than the skills-based matchmaking system.

Thus, although there are still some matches created did not meet the expectation of the players, but there are more matches created by the traits-based matchmaking system let the players enjoy more in the in the gamming sessions.

6. Conclusions

Matchmaking is the process through which the system groups players into opposing teams for gamming sessions. Currently, Dota2 use MMR-based and seasonal ranking medal matchmaking system to put players into teams. This type of matchmaking system is group into skills-based matchmaking system. Skills-based matchmaking system put players into groups by matching players with equal skills level together.

In MMR-based matchmaking system, each player is given a MMR values that represents their skills level. A range of MMR values is group into a rank. The players that have their MMR values in the same ranks will be put together into teams in a gamming session by the matchmaking system. Seasonal ranking medals represents the level of skill a player achieves in a single season. It is determined by player's MMR values and other some hidden factors. The ranking medals will reset after each season.

The current skills-based matching system of Dota2 may not be the most effective matchmaking available. When matchmaking, players may not have balanced roles in a team. This is because every player has their own playstyles and their own roles that they excel in. It is also common that some players tend to balance the roles in the team by using the roles that they are not familiar with.

Player's traits-based matchmaking system is a matchmaking system that groups player together into teams based on the general-based behaviors that can describe players more effectively. The traits-based matchmaking system not only can be used in Dota2 matchmaking system but also can be use in other games because of the general-based behaviors use for profiling. With this matchmaking system, more balanced teams can be form from a group of players. Players will less likely to suffer from unbalanced teams in a team. Players will also be able to enjoy the gamming sessions with the teams created by the traits-based matchmaking system.

To create a player's traits-based matchmaking system, a useful player's profile is needed to get data for the matchmaking algorithm to match players into team more effectively. A certain set of metrics that can describe personal behaviors is listed. Then, a feature extraction algorithm is created according to the most appropriate metrics to describe the player's behaviors. Player's profile is then created for each player based on the metrics decided. An optimized matchmaking algorithm is created to put players into teams by using player's profile. Lastly, a universal evaluation system is used to show that the traits-based matchmaking system is more effective than skills-based matchmaking system.

From the evaluation system for the player's traits-based matchmaking system, the result show that the player's traits-based matchmaking system is better than the skills-based matchmaking system. The players had a more enjoyable gamming sessions by using the teams and matches created by the traits-based matchmaking system compare to the skills-based matchmaking system.

From the feedback from the evaluation system for the traits-based matchmaking system, there are some of the matches that do not meet the player's expectation. This is because that the current attributes use for players profiling are determined through heuristic due to lack of baseline. By adding more attributes into the profiling algorithm may improve the result of the traits-based matchmaking but that is beyond the scope of this project. In the future, more attributes may add into the profiling algorithm so that the matchmaking system can create more balanced matches and let the players more enjoyable in the gamming sessions.

The current player's traits-based matchmaking system only can be used for the games that are English version games. Therefore, the matchmaking will not work for other games that are not using English language. This is because the matchmaking system which use text mining technique to collect data use for the profiling algorithm only recognized English language. Thus, the player's traits-based matchmaking system may be improved to support other language of games in the future.

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