Valorant VCT 2022 Player's Playstyle Analysis

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"Every person is a teacher, every house is a school"
- Ki Hadjar Dewantara

All material in this paper are available in clearer image here:
https://github.com/prakhosha/Valorant-VCT-2022-Player-s-Playstyle-Analysis

Abstract

The increasing popularity of the tactical shooter video games called *Valorant* has brought the video game into one of the most played first-person-shooter video games today. Partly, this is because every character in *valorant* is unique. This popularity also spread into the e-sport scene. One e-sport event named *Valorant Champions Tour (VCT)* is the most prestigious *Valorant* e-sport tournament in the world. One thing that is interesting in *Valorant* e-sport is how every player and team seems to have a different playstyle of their own. Much like football that have goalkeeper, defender, midfielder, and forward, *Valorant* also have duelists, initiators, controllers, and sentinels. And much like football where a forward can be a false nine or a target man, an initiator in *Valorant* also has a different playstyle. There are initiators who take fights aggressively and there are also initiators who use abilities to help their teammates. This paper will try to find the similarities in playstyle between all players that participated in *VCT 2022 Champions*. We find that there are 6 groups of different playstyles for all professional players.

Keywords: video games, valorant, t-sne, e-sport, behavior analysis.

Introduction

Video games have been part of a lifestyle of modern society. Not only younger people, there are young adults and adults who play video games after their work day or on the weekend. One video game that has been at the top of popularity is *Valorant (Knudsen, 2023)*.

Valorant is a tactical shooting video game where players can form a team of 5 to fight other teams. The difference between *Valorant* and other tactical shooting video games is that valorant provides unique characters called agents that we can use. Every agent has their own abilities. For example there are agents that are good when attacking, there are agents that have good abilities to help their teammates, and there are agents who are good at defense situations.

Not only in the casual scene, the increasing popularity is also occurring in the professional scene *(Valorant - Esports Viewership and Statistics, n.d.)*. VCT is the biggest *valorant* e-sport event in the world. Last year, the *VCT 2022 Champions* was held in Istanbul, Turkey. There are many talented professional players from many teams competing in this scene. Much like professional football with their division of goalkeeper, defender, midfielder, and forward, agents in *Valorant* are divided into duelists, initiators, controllers, and sentinels. And just like a forward in football can be a false nine or a target man, an initiator in *Valorant* can be played aggressively or passively using their utilities to help their teammate. As a result of this, there are different playstyle many for all professional players in *Valorant*.

This paper will try to find and group those different playstyle. It should be noted that although there are *Valorant* professional players that played better than others, this paper will not try to accommodate data that indicate how good of a shooter someone is.

Data and Methods

The data that will be used comes from *vlr.gg*. There are about 81 professional players from 16 different teams from all over the world. The data consists of:

1. player_name: Player name
2. player_url: Link to players profile on vlr.gg
3. player_RND: How many rounds the player played
4. player_rating: Player rating
5. player_ACS: Average combat score
6. player_KAST: Kill, assist, survive, trade %
7. player_KD_ratio: Kill-death ratio
8. player_ADR: Average damage per round
9. player_KPR: Average kill per round
10. player_APR: Average assist per round
11. player_FKPR: First kill per round
12. player_FDPR: First death per round
13. player_HS: Headshot %
14. player_CL_percentage: Clutch success %
15. player_CL: How many clutches the player won / how many clutches the player played
16. Three agents picks for every player

Analysis of The Available Stat

This analysis is supposed to analyze a player's playstyle without considering their ability in the game. So to accommodate this, pearson correlation of all parameters in the game will be computed to the player rating as player rating is an indicator on how good a player is in playing the game. Any parameter that performs above 0.5 of pearson correlation will then be removed. Figure 1 shows the result of the correlation.

Figure 1. Pearson correlation of all parameters to player rating.

Although player headshot percentage does not indicate any correlation to player rating, it is still better to remove this from analysis because it is an indication of how good the player is at aiming.

Also, while the correlation shows that player's clutch percentage does not correlate with player rating that much, putting it in analysis would be unfair judgement because this parameter still contains information about how good someone is at winning the round.

Thus, I suggest creating a new parameter called clutch situation frequency or CSF for short. This new parameter can be obtained by dividing the number of clutch situations they have played by the number of rounds they have played. The result of the correlation is shown in Figure 2.

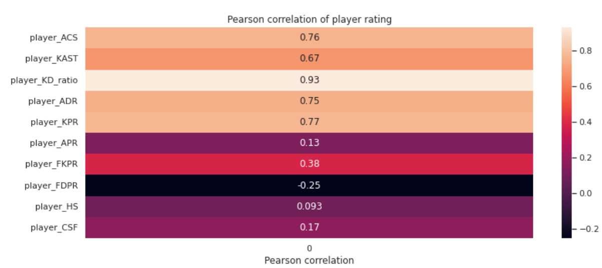

Figure 2. Pearson correlation of all parameters with the new CSF with player rating.

As you can see, our new CSF parameter does not have any correlation with player rating. Based on this result, we will use APR, FKPR, FDPR, and CSF to analyze a player's playstyle.

Also, because the data in *vlr.gg* can only show 3 agents that the player played. And there is no indication of whether those agents are the most used agents by the player or not. So, it is best to remove the agent pool from the analysis.

APR, FKPR, FDPR, and CSF Distribution for All Professional Players

The distribution of APR, FKPR, FDPR, and CSF are shown in Figure 3.

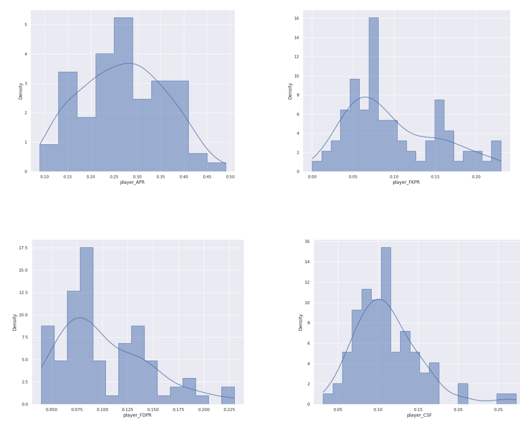

Figure 3. APR (top left), FKPR (top right), FDPR (bottom left), and CSF (bottom right) distribution for all players

Assist per round (APR) for all players through *VCT 2022 Champions* is distributed normally. First kill per round (FKPR) for all players through *VCT 2022 Champions* is not normally distributed. And it makes sense because FKPR a little bit relies on how skilled the player is so there are abnormalities on the data. Clutch situation frequency (CSF) also suggests an abnormal distribution.

The interesting thing is that based on FKPR it should be expected that the distribution of FDPR would be left-skewed (because abnormal players that successfully entry should live longer than most players so result in small FDPR), but in fact it is right-skewed.

In my opinion, this is because in defensive situations, most players tend to sit deep holding an angle while some of them hold a dangerous position resulting in right-skewed data. This just shows that FPDR is one way to measure how aggressive a player is.

Manifold Learning using t-SNE

Manifold learning is a type of machine learning algorithm that can reduce the dimension of a data and reveal any useful information about the data *(Melas-Kyriazi, 2020)*.

There are many types of manifold learning, one of which is t-distributed stochastic neighbor embedding (t-SNE). This algorithm will transform the manifold from high dimensional space to lower dimensional space based on conditional probabilities of the data *(Maaten & Hinton, 2008)*. The excellence of t-SNE compared to other dimensional reduction is that t-SNE will try to maintain the information that is contained in local space more.

Before the can be input to t-SNE, it would be best if we scale our data so that all parameters are in the same range. Thus, standard scaling and principal component analysis (PCA) will be applied to the data before t-SNE. The result of the t-SNE algorithm is shown below as Figure 4.

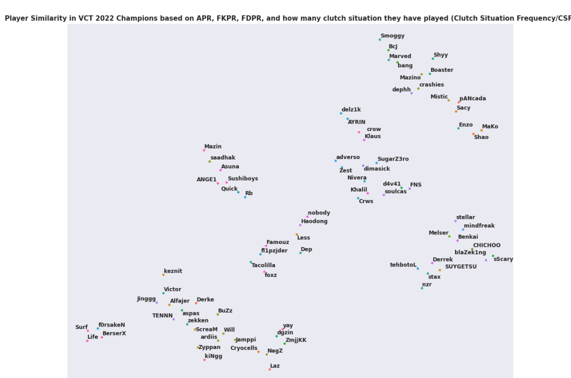

Figure 4. The result of the t-SNE algorithm. It seems like there are 6 different groups of playstyle.

Analysis

Visually we can see there are about 6 different groups of playstyle as shown in Figure 5.

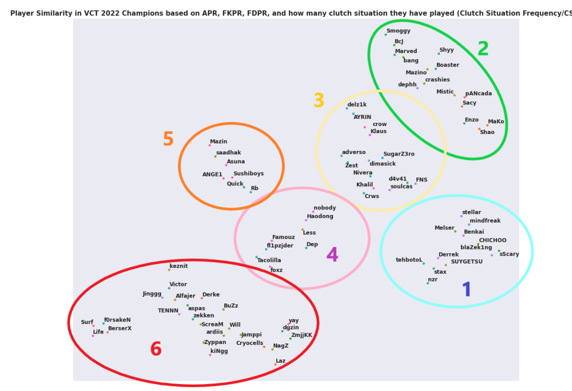

Figure 5. Grouped result of t-SNE algorithm.

The Interpretation of the group is present below. It should be noted that direct utilities do not mean utilities in general. direct utilities means abilities that result in assist. As for abilities that do not result in assist such as those to take space, to hold space, or dummy abilities do not count in direct utilities.

The first group of players usually play as the deepest member in a site or the last one to entry a site and also tend to use direct utilities to help other members. This is true because professional players like *mindfreak*, *SUYGETSU*, or *sScary* more often than not are the last member of their team to survive. This is also backed with the CSF distribution that has been grouped below.

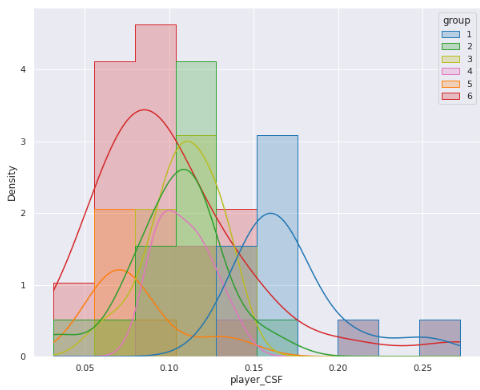

Figure 6. Distribution of CSF grouped.

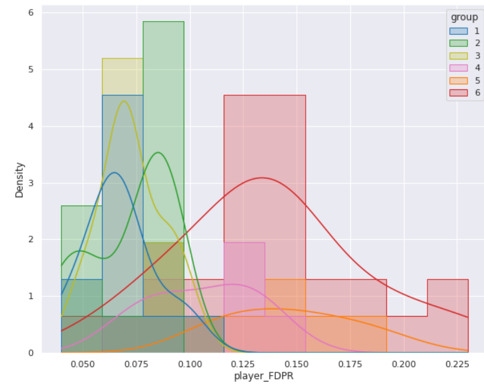

Figure 7. Distribution of FDPR grouped.

From Figure 6, we know that group 1 has the highest CSF among all groups. This means group 1 is more likely to experience clutch situations and thus has the highest chance of being the last surviving players.

Group 2 consists of those who play safely or passively and is the most likely group to use direct utilities (utilities that result in assist) to help other members. (except for *Smoggy*, the reason he is here is because he did not experience many first deaths as *Jett* and he also made many direct utilities as *Kay/o*). This might be true because players such as *pANcada*, *Boaster*, or *Shao* tend to have higher assists than average players. This is also backed by the distribution of CSF above and also FDPR and APR below.

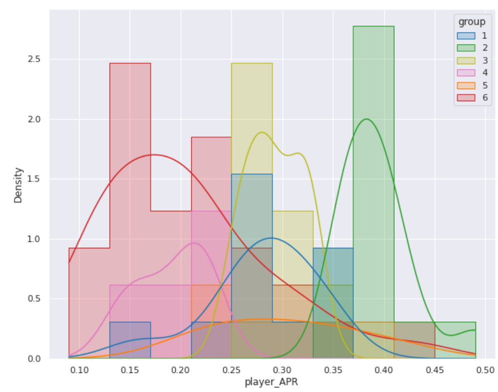

Figure 8. Distribution of APR grouped.

CSF distribution indicates they often experience clutch situations but not so often as group 1. FDPR of group 1 also suggest they are safe so they are not experiencing many first deaths. And lastly as APR distribution shows, this group of players has the highest direct utilities usage.

The third group of professional players tend to play safely or passively and use direct utilities to help other members. This can be seen by how low their FPDR are and their APR is also high but not as high as group 2. They also have low FKPR, as indicated in

Figure 9, which is an indication that they are not playing aggressively as others.

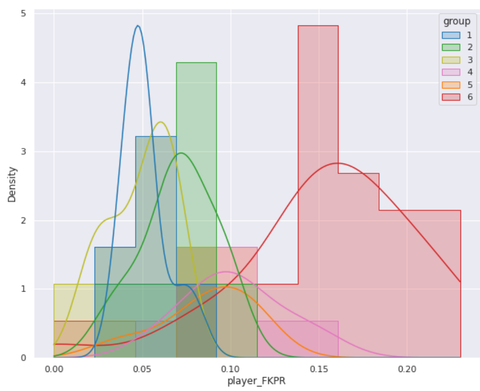

Figure 9. Distribution of FKPR grouped.

The next group of players, which is group 4, tend to play aggressively or to hold a dangerous position. This can be seen by how high their FDPR and FKPR is compared to other groups. This group is also the least likely group to use direct utilities other than the space taker (group 6) as seen by their APR.

Group 5 consists of players that tend to play aggressively to be able to use direct utilities to help other members or tend to hold a dangerous position. This can be seen by how high their FDPR, FKPR, and APR (compared to group 4) is.

Lastly, group 6 consists of players that are designated as the space taker for the team and are the first contact players (tend to hold a dangerous position). This is the most aggressive group compared to other groups. This can be seen by how high their FDPR and FKPR is. This group also has the lowest CSF and APR compared to any other group.

Conclusion and Suggestions

Player's playstyle of *VCT 2022 Champions* has been successfully analyzed using t-SNE algorithm. The result shows there are 6 groups of playstyle in the competition. The intent of this paper is not to determine what kind of playstyle is the best to win the tournament, as valorant is a complex video game and different teams have their own playstyle. This paper however can be used by professional teams from all over the world. They can use this method of analysis to determine whether or not they are going to sign a player. The team can also use this analysis to take a look at their own team and determine what kind of player that they need in their team.

I do acknowledge that there are still many flaws in this analysis. The removal of agent pools from analysis makes *Smoggy*, the space taker and initiator of his team, that played Jett and Kay/o being grouped into group 2. Thus, I suggest adding an agent pool for further analysis. This will incorporate agents pool as an indication of different playstyle.

I also suggest adding a new parameter that shows when the player died in a round as a respect to their teammate. So we will be able to know who is the second or third or so player to die in their team. Adding this to the analysis will show who is the one that is designated as the trader for the space taker or who is the one that plays passively in a site execution.

Nevertheless, I think this analysis has shown a decent success grouping the playstyle of *VCT 2022 Champions* professional players.

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