PLAYING STYLES IN STARCRAFT

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ABSTRACT

Understanding playing styles in video games may assist game designers to create entertaining game content for different players. Numerous factors determine how distinct players may approach a game, e.g., player preference, game literacy, and player motivation. In Real-Time Strategy (RTS) games, for understanding player behaviour, it is particularly important to model player preferences and adopted game strategies. As such, as a continuation of previous work, the present paper investigates how distinct human players approach the popular *StarCraft* game in terms of preferences and strategies that may be inferred from game observations. In particular, we investigate how distinct match-types relate to the different playable races in the game. To this end, we propose features that reflect playing style, and uncover unique variations in playing style by means of Principal Component Analysis (PCA). Findings of experiments with clustering player styles of *StarCraft* players reveal that playing styles can indeed be distinguished in different match types. While one may expect playing style to affect the chance of winning, results reveal win probability is not significantly affected by player style, but the length of matches is.

INTRODUCTION

Gaining an understanding the variations of the playing styles of players of video games, may assist game designers to customize the game content based on the behaviors of their player base. For instance, some studies explored players' ingame behavior (Bateman et al. 2011) to determine how a game can entertain different player types. Previous research investigated the development of a general model that fits a variety of games (Bateman 2009; Yee 2006), or a model applicable to specific games (Drachen et al. 2009; Gow et al. 2012). In our study, we explore playing styles in the popular Real-Time Strategy (RTS) game *StarCraft*.

In RTS games, players generally have plenty of commands at their disposal, that can be enacted at every iteration of the game. In *StarCraft*, players can build various buildings and create different units, while units can perform different actions. A high variety of playing styles is possible by choosing the type and order of buildings, by preferring certain units over others, and by using units in different ways. Therefore, players may play the same game in different ways, which we here informally refer to as different playing styles.

StarCraft includes different race types: Terran (T), Protoss (P), and Zerg (Z). At the start of the game, players may choose one of the races to play with. Races have different unit types and command types. We expect that playing styles are related to the race used by a player, and probably also to the race used by the opponent. For human vs. human matches, six match types are possible: (i) Protoss vs. Terran (PvT), (ii) Protoss vs. Zerg (PvZ), (iii) Terran vs. Zerg (TvZ), (iv) Protoss vs. Protoss (PvP), (v) Zerg vs. Zerg (ZvZ), and (vi) Terran vs. Terran (TvT).

In previous work (Norouzzadeh Ravari et al. 2016), we investigated winner prediction in *StarCraft*. We showed that the top-10 features used for winner prediction are more or less the same across all match types, but there are some notable exceptions, which, as we concluded, depend on the match type of the game.

In this paper, we will further analyze the playing styles in *StarCraft* in relation to match types. We will discuss a new feature set that we propose to distinguish playing styles. The feature set reflects what kind of commands the players use during a match. In brief, in this paper we will answer the following three questions:

1. Are there distinctly different playing styles in *StarCraft*?
1. Do playing styles differ across the match types?
2. Do playing styles differ across the races?

Next, we will discuss literature that is relevant to the topic of the present paper.

RELATED WORK

Different players employ different playing styles. To distinguish different players, several attempts have been made to define playing styles. Researchers looked at players' in-game behavior and players'personalities. Bartle (Bartle 1996) proposed one of the first divisions of playing styles. According to his study, playing style has two dimensions: action vs. interaction and player-orientation vs. world-orientation. Later another study (Yee 2006) reported that Bartle types are not a general prototype, and that they suffer from biases.

The connection between playing style and in-game behavior was made by multiple researchers. Others (Drachen et al. 2009) modeled players' behavior in *Tomb Raider Underworld* and they observed four playing styles.

Reseachers (Gow, et al. 2012) also studied playing styles in *Snakeotron* (an arcade game with a highly limited state space) and *Rogue Trooper* (a third-person shooter game). Playing styles is also studied in *Battlefield 3* (Normoyle and Jensen 2015), and authors found that a player can have multiple playing styles simultaneously.

Few studies have been done on playing styles in RTS games. Bakkes (Bakkes et al. 2009) adopted a case-based approach to model opponent players based on behavioural-similarity metrics. Si (Si et al. 2016) conducted a study on map exploration style in *StarCraft*.

In our previous research (Norouzzadeh Ravari et al. 2016), we found that a general model can predict the winner across all of the match types in *StarCraft*. As such, in the present paper, we propose different feature sets based on match types that exceed 300 features for each player. This feature set is subsequently reduced and analyzed by employing Principal Component Analysis (PCA). We will build on the top Principal Components (PCs) to show how playing styles vary across the match types. Next, we will employ *k*-means clustering for grouping together playing styles accross match types.

Table 1: Specification of the *StarCraft* Dataset

	PvT	PvZ	TvZ	PvP	ZvZ	TvT
Players	4032	1680	1624	748	398	790
Features	511	479	533	371	380	416

DATA

We use a *StarCraft* dataset of expert players (Robertson and Watson 2014); it included approximately 4,000 full replays that the most of players have played only in a single match. An overview of the number of players available in each of the match types is provided in Table 1.

For the purpose of the present analysis, features are defined per race type. Since possible actions vary based on race type, the number of proposed features vary based on the race type. Table 1 shows, besides the number of players, also the number of features per match type. The features encompass the type, frequency, distance to the base, and the number of units that are involved in an action that the player used. We chose these features to discover the role of action attributes in addition to the action type. Given a large number of possible features to investigate, we employ a subset of the features for our analyses. Specifically, for each action, the following features are extracted:

- *Action frequency*: for each player, how many times an action is repeated during the match up.
- *Group size*: how many units the player associated with an action.
- *Group size variance*: to represent the variety of size of groups that are used in the style of player.
- *The number of unique groups*: players can use a group many times, or they create different groups for different tasks.
- *Mean and variance of distance between base and target*: the location of units that perform an action gives useful information. For each action, we computed mean and variance of normalized distance between the primary base and group target.

ANALYSIS

In this section, first we describe feature dimension reduction and feature analysis by PCA. Subsequently, the results of clustering playing styles are given, and the relationships between playing styles, wins/losses and game-length are presented.

Analysis of playing styles using PCA

Our analysis of playing styles builds upon PCA; it is a statistical procedure that is widely used for dimension reduction and for discovering discriminative features (Van Der Maaten et al. 2009). We analyzed our features by PCA to discover playing styles across the match types. We limited ourselves to the top-2 components, and we keep the PCA coefficients above 0.1 to focus on the strongest features.

The result of PCA analysis reveals that top-2 coefficients cover between 37% to 45% of the variance of the features in all of the match types. As such, top PCs can be considered the most discriminative features for distinguishing playing styles. In the following sections, we discuss in detail the most discriminative features for non-symmetric match types (different races playing against each other) as well as for symmetric match types (races playing against themselves).

Analysis of non-symmetric match types

We examined the top PCs for non-symmetric match types (PvT, PvZ, and TvZ) to find the most discriminative features that distinguish playing styles. We found that for the match types PvT and TvZ, the top PCs cover 23% of the variance of features for each of the races involved. For the TvZ match type, it covers 29% of the variance of features, for both of the races involved. For all match types, the second PCs cover between 14% and 17%, while all other PCs score considerably lower. Therefore, it makes sense to focus first and foremost on the top two components, as they cover the major playing styles.

We note that the top PCs in PvT include `research' and `upgrade' commands, while these commands are missing in the top PCs in PvZ and TvZ match types, which seems to indicate that when Zerg players are involved in a match, research and upgrades have little influence on play style. Moreover, we noted that the `train' command is found in the top PCs in all non-symmetric match types. Interestingly, the first PC includes some commands that are limited to a specific race, such as `siege', `unsiege', and `lift' (for Terran) in PvT and TvZ; and `burrow', `unburrow', and `morph' (for Zerg) in TvZ and PvZ. This demonstrates clearly that playing styles depend partially on the race type.

Analysis by race type

We observed that playing styles notably vary in non-symmetric match types. In this subsection, we figure out whether playing styles in a match type differs based on the opponent's race type. As such, we cluster playing styles of each race type in a match type. For instance, in PvT match type, we repeat the earlier described clustering procedure to

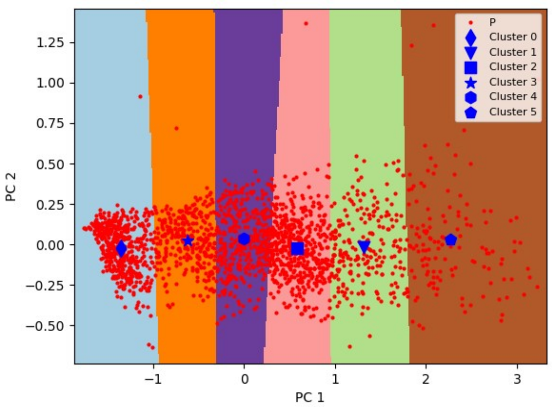

Figure 1: Clustering of Playing Styles of Protoss Players in PvT Matches

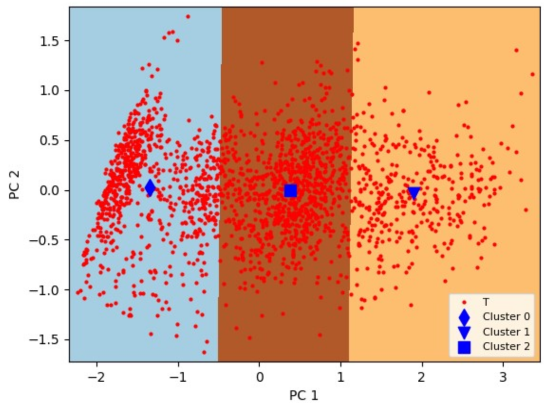

Figure 2: Clustering of Playing Styles of Terran Players in PvT Matches

discover to what extent playing styles within the Protoss and the Terran race are different.
Figures 1 and 2 show clusters of Protoss and Terran players in PvT matches. Protoss playing styles are clustered into 6 clusters, and Terran playing styles are clustered into 3 clusters. This observation shows that the variety of playing styles of the Protoss race is larger than that of the Terran race in PvT matches.
Figures 3 and 4 show the comparison of discriminative features in these races. Each feature label is replaced with the equivalent command code; Table 2 shows the complete list of command codes and feature labels. In Figure 3, we observe that the mean value of some features is close to zero because these commands are limited to Terran race, such as command codes 22, 23, 24, 132, and 139. Interestingly, cluster 2 has the lowest mean of values among all of the features, but at the same time, the difference between mean values of features in the other clusters is more or less the same across all of the features. The highest value of the features belongs to the commands 4, 7, 12, and 13, respectively. In Figure 4, cluster 1 has the lowest mean of feature values. For Terran players, the commands 4, 7, and 12 also have high values, just as the Protoss. Generally, we observe that some commands are used in both races with the similar frequency.

Clustering playing styles

When designers wish to tailor the game experience to a group of players -- or have the game design be informed by observing distinct behaviors -- it helps if they can determine discrete groups of players, each group fitting a particular playing style. To automatically determine such groups for *StarCraft* players, we emploeyd *k*-means clustering procedure. The features listed in the Data section used for clustering after normalization.
To get an impression of the required number of clusters, we utilized the Calinski-Harabasz (CH) criterion (Caliński and Harabasz 1974); it is a common clustering optimization criterion that has been used successfully for cluster analysis (Maulik and Bandyopadhyay 2002). Building upon this method, we varied the number of clusters from 2 to 14 and examined the CH index values. We observed that the CH value has a peak at 4 clusters.
The extracted feature set is high-dimensional. We therefore employed PCA for dimension reduction. We found that PCA with two components covers more than 37% of the variance of features. Therefore, we used the top two PCs in k-means from the scikit-learn package in Python for clustering.
In non-symmetric match types, we examine playing styles by two approaches: principal component analysis of playing styles without considering the race type of the opponent (opponent-independent) and principal component analysis of playing styles by considering the race type of the opponent (opponent-dependent).
Playing styles in non-symmetric match types are presented for PvT matches in Figure 5. The top two PCs for each of the match types determine the axes. We observe that the players from different race types are generally placed in different clusters. For instance, in Figure 5 Protoss players are mostly located in clusters 0 and 1, while Terran players belong to clusters 2 and 3. Therefore, we conclude that the playing styles between each of two races is different. Moreover, the results suggest that also within race types there are different play styles possible. A comparison between dispersions in different match types shows that dispersion in PvT is lowest, which means that in a PvT match similarity in playing styles within a race is highest.
We observed that different races have different playing styles. To discover playing styles in a race, firstly we separate players in a match type based on their race type. Then, we utilize PCA to find more informative features for each race. We keep the PCs above 0.1. Next, we select the top-two PC, which together cover more than 39% the variance of the features.
In PvT matche types, the first PC in the both races have some commands in common such as `research', `upgrade', and `train', but there are some differences too. For instance, Terran components include `siege' and `unsiege' (which are Terran-only commands). The Protoss top PCs include `use tech' and `train fighter,' which are not included in Terran components. The top PCs of Protoss and Zerg players in PvZ matches share `research', `upgrade', and `train' commands, but the `use tech' command is only included in the Protoss component. The Zerg top PCs include the Zerg-only `burrow', `unburrow', and `morph' commands.
In TvZ matches, the top PCs of Terran and Zerg players show more dissimilarities than similarities. They only share the `train' command. The top components of Terran include besides the Terran-only `siege' and `unsiege' commands, the

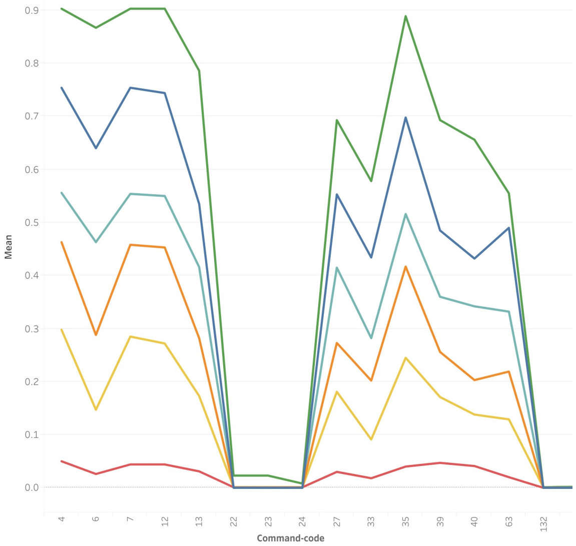

Figure 3: The Comparison of Discriminative Features' Mean of Protoss Clusters in PvT Matches

general commands `research', `upgrade', and `use tech.' The Zerg player's top PC, besides `train,' are limited to Zerg-only commands such as `morph', `burrow', and `unburrow'.

Playing styles in symmetric match types

In symmetric match types, the players can build the same buildings and select the same commands. While the players could potentially use exactly the same playing styles, we found that there are still variations of playing styles employed.

For each of the match types, we separated the players according to their race type and performed once more a PCA analysis and *k*-means clustering per race. For the resulting clusters, each of which arguably represents a different style, we calculated the average win-loss ratio and average game length. The results are summarized in Table 3 for non-symmetric match types. We removed the results for symmetric match types due to the space limitation.

In Table 3, playing styles, the win-loss rate, and mean game-length are presented for each cluster in non-symmetric match types. We used the Wilcoxon ranksum test, finding that for each race type the game-length between most of the clusters are significantly different ($p < 0.05$). The clusters of Terran players in PvT have the same properties; that is, while the

Table 2: Command Code of Each Feature Label

Code	Label	Code	Label
4	Train	28	Unload All
6	Research	33	Cancel Construction
7	Upgrade	35	Cancel Train
12	Hold Position	39	Rally Point Unit
13	Stop	40	Rally Point Tile
16	Return Cargo	63	Train Fighter
18	Burrow	132	Place Mine
19	Unburrow	139	Cast Scanner Sweep
22	Siege	142	Cast Psionic Storm
23	Unsiege	143	Cast Irradiate
24	Lift	145	Cast Consume
27	Unload	147	Heal Move

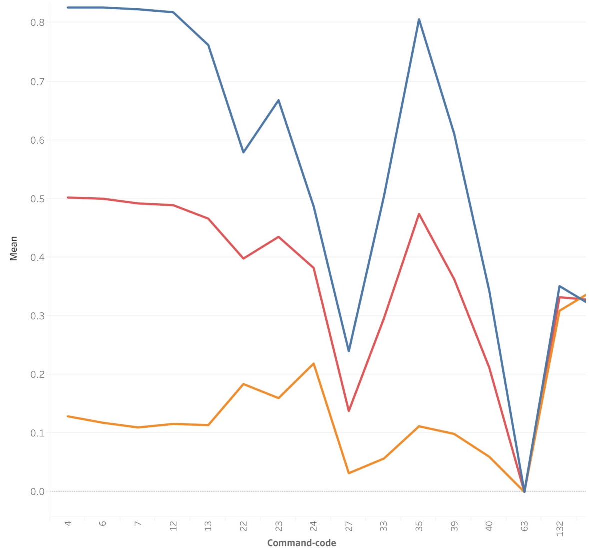

Figure 4: The Comparison of Discriminative Features' Mean of Terran Clusters in PvT Matches

win-loss rates are similar, the game-lengths vary. Interestingly, the clusters of players of PvZ and TvZ matches also have comparable win-loss ratios, and varying game-lengths. In summary, we may conclude that playing styles affect game-length.

However, the win-loss ratios for none of the match types differed significantly from each other. While one might be tempted to think that Protoss players have a higher chance of winning than Terran players in PvT matches, and that Terran players have a higher chance of winning than Zerg players in TvZ matches, a Wilcoxon rank sum statistical analysis shows that the differences between all ratios are not significant at $p< 0.05$. We found that similar conclusions held for symmetric match types, i.e., game lengths differed significantly in most cases, while win-loss ratios did not.

CONCLUSION

This paper investigated playing styles of *StarCraft* players, insofar they relate to match types. We found that there are definitely different playing styles available to players, which are partially -- but not completely -- based on the commands that are unique to a race, and the opponent race. Even when a

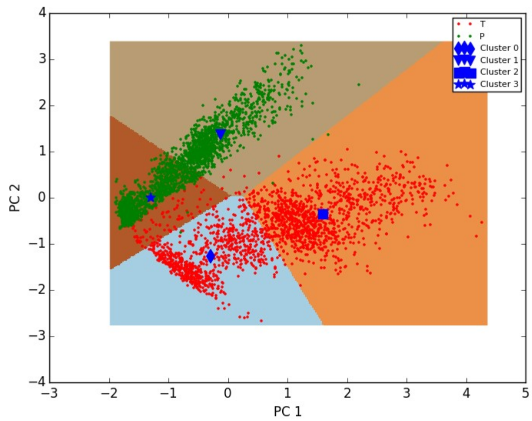

Figure 5: Clustering of Playing Styles in PvT Matches.

race plays against itself, different playing styles are used.

We found that for the expert players, choice of playing style does not influence their win-loss ratio, though it does influence game length.

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Table 3: Comparison of Win-Loss and Game-Length (mean-gl and std.dev in minutes) in Non-Symmetric Match Types. The Last Column Denotes with which Clusters there are Significant Differences for Game Length (p <0.05))

Matc Type (#players)	Cluster	#players	Win-loss	mean-gl	std.dev	Significantly different from
PvT (4032)	P0	504	1.16	24	9.6	P1, P2, P4
	P1	480	1.35	28	9.5	P0, P3, P4, P5
	P2	228	0.96	29	10.5	P0, P3, P5
	P3	370	1.05	25	10.2	P1, P2, P4
	P4	130	1.28	32	16.6	P1, P3, P5
	P5	304	0.97	23	10.6	P1, P2, P4
	T0	360	0.87	28	10.6	T1, T2
	T1	895	0.88	27	11.8	T0, T2
	T2	761	0.88	24	10.4	T0, T1
PvZ (1680)	P0	158	1.13	28	13.8	P2, P4, P5
	P1	125	0.86	29	10.1	P2, P4, P5
	P2	163	0.66	18	7.6	P3, P4, P5, P6
	P3	85	1.18	29	10.8	P2, P4, P5
	P4	30	1.14	39	18	P0, P1, P2, P3, P5, P6
	P5	121	0.75	21	10.2	P0, P2, P3, P4, P6
	P6	158	1.05	27	12.8	P2, P4, P5
	Z0	470	1.04	21	10.7	Z1
	Z1	370	1.15	31	12.6	Z0
TvZ (1624)	T0	212	1.19	27	9.7	T1, T2
	T1	271	1.13	22	9.2	T0
	T2	329	1.23	22	7.9	T0
	Z0	302	0.97	23	8.2	Z1, Z2
	Z1	370	0.79	21	8.9	Z0, Z2
	Z2	140	0.72	29	8.4	Z0, Z1