Playstyles in Tetris: Beyond Player Skill, Score, and Competition

Stéphanie Mader(✉) and Eloïse Tassin

Conservatoire National des Arts et Métiers, CNAM-CEDRIC, ILJ, 292, Rue Saint Martin, Paris, France
stephanie.mader@cnam.fr
https://cedric.cnam.fr

Abstract. In this study, we looked at playstyles in Tetris in order to explore how players construct meaning in abstract video games. To do this, we looked at playstyles that go beyond metrics related to player skill, score and competition. Indeed, non-expert playstyle are often neglected in playstyle studies, but construction of meaning can also occur in non-competitive playstyles. We logged the play of 31 Tetris players and used Principal Component Analysis to model their playstyles. In doing so, we discovered 4 distinct playstyles that we present in this paper.

Keywords: Playstyles · Player models · Game logs · Telemetry · Tetris

1 Introduction

In this paper, we present preliminary results from our work modelling the playstyles of Tetris players. Playstyle can be defined as the way someone plays a specific video game. Most video games provide degrees of freedom in their interactions, giving options to players to tailor their experience in this possibility space through their playstyle [1,12]. Beyond this, players can also define their own goals while playing, sometimes subverting the game. Tekofsky et al. define playstyle as "any (set of) patterns in game actions performed by a player." [11].

This study is part of a research project exploring how players construct meaning while playing abstract video games. For this, we created 3 variations of the game Tetris, a widely popular arcade action-puzzle video game. We changed a

This study is part of a project supported by Région Ile-de-France (Appel DIM-RFSI 2020). The authors thank everyone whose work on the transdisciplinary Tetris-20 project indirectly contributed to this publication: Vinciane Zabban, Fanny Georges, Leticia Andlauer, Sophie Bemelmans, Elisa Massip. The authors would also like to thank Nicolas Piñeros for kindly helping us to conduct part of our study at the Ludomaker gamelab.

B. Göbl et al. (Eds.): ICEC 2022, LNCS 13477, pp. 162–170, 2022.
https://doi.org/10.1007/978-3-031-20212-4_13

few game rules to provide a different game experience and meaning. Even though the gameplay of Tetris seems constricted, through 6 preliminary interviews and observations of players, we found out they played more diversely than expected. Only one of them was playing as intended by the designer and interpreted the meanings. This prompted us to model playstyles as an important criteria to analyse how playstyle and meaning creation interacted in such video games.

Many studies have been done on Tetris; the studies about playstyle focus on player skill and score [5,10]. These studies distinguish between expert and novice players but do not analyse novice players in details. We observed that playstyle studies on other games also neglected non-competitive players [2,9,11].

As construction of meaning can also occur in non-competitive and novice playstyles, we looked at playstyles metrics beyond those related to player skill, score and competition. In this paper, we present the results of this first exploration. We extracted the game logs of 31 players of Tetris totalling 110 games played among three different Tetris variations and then used Principal Component Analysis on 23 quantitative variables and 4 qualitative variables.

2 Background

Since Bartle's typology of MUD players in 1996 [1], many approaches have been used to model players such as typology of play preferences from surveys [12], profiles based on psychological models [8], or player skill model [7]. Here, we focus on approaches using primarily game logs to study playstyles. Apart from the practicality of having access to game logs, one challenge lies in the large amount of data generated by game logs. Players data need to be aggregated into variables calculated from the addition of small game events or accumulated through time. Moreover, Karpinskyj et al., in their survey of video game personalisation techniques, noted that game logs alone only produced objective facts about events in the game and were difficult to use for more interpretative analysis [4]. This challenge of interpreting data has also been noted by Drachen et al. in their comparative studies of clustering methods for game logs. The authors even used the method capability at providing interpretable behavioral profiles as their main comparison criteria between clustering techniques [3]. Indeed, Principal Component Analysis (PCA) with clustering techniques such as k-means can be used to define groups of players, but the resulting groups can be more or less easy to interpret, and in our case, to translate into playstyle.

Some studies about playstyles use game logs and clustering techniques but the authors either defined the main playstyles beforehand, or did not provide interpretation of the profiles. Bialas et al. linked playstyles of Battlefield 3 to cultural differences [2], Tekofsky et al. tried to correlate playstyle with the player age [11], and Norouzzadeh Ravari et al. used PCA to study playstyles of expert players of Starcraft [9]. Those studies provide important results about what influences or not playstyles, but they feature a top-down approach to playstyles and their objects of study are competitive multiplayer video games. Resulting in analysis and playstyles weighted towards player skill, score and winning strategy.

If Tetris can be played as a competitive multiplayer video game, our study concentrates on its use as a solo video game. Tetris has been used in numerous studies from different disciplines. A few of them use in-game data logging to profile players generally to feed a dynamic difficulty adjustment algorithm with the objective of helping the player reach an optimal experience or flow (see [6] or [10] for examples). We found one Tetris study using a method similar to ours; Lindstedt and Grey studied how to distinguish between expert and novice players using PCA on game logs [5]. They identified three main components connected to scoring: disarray, 4-line planning, decide-move-placed.

Regarding the current literature on the topic, the main originality of our work is that we aim at discovering non-competitive Tetris playstyles. Indeed, if most game definitions include some notions of challenges and conflicts, players do not always abide by those rules. As a result, their playstyle can be more diverse than expected even in a seemingly simple arcade action-puzzle game such as Tetris. Current studies analysing playstyles appear to overlook player agency to determine their own play objective and success independently of the score and game rules. Playstyle being the manner players play a game, we argue the importance of not equating playstyle to skill. Skill is about player ability to do something well, and is, along challenge, difficulty, and their connections to learning and flow, an important and vastly studied topic. Competitive playstyles allow to categorise and describe the manners players play to win or score, but those are not the only kind of playstyles. In this study, our objective is to explore the existence of playstyles in Tetris beyond player skill and competition.

3 Tetris and Our Variations

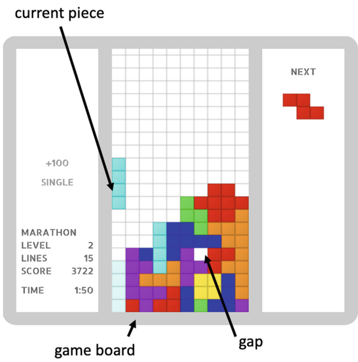

Fig. 1. Screenshot of the Tetris game used in this study.

In Tetris (Fig. 1), the player stacks pieces (also called tetrominos or zoids) until they loose because a piece can not be placed entirely in the game board, or win because they reach a specific objective of time, score, or number of lines depending on the game mode. A piece is always composed of 4 blocks (or squares) and there are 7 different pieces. If the player can stack the pieces to have one or more complete lines, they disappear, give points that accumulate in a score (depending on the number of lines done among other parameters), and the blocks above come down the same number of lines. Players can leave gaps in the game board that they will need to clean to make lines. The piece they control comes down automatically at a linear speed that augments each time they pass a level by making 10 lines. Players can only rotate the piece (right or left), translate/shift it (right or left), or make it descend more quickly (soft drop) or instantly (hard drop). An episode starts at the appearance of a piece and ends when the piece is placed on the game board. A game or a run encompasses everything from the appearance of the first piece to the win or loss of the player, forcing them to restart a run if they want to continue playing. Clearing 4 lines at the same time is called a 4-line or a Tetris, it requires the use of the bar-shaped piece.

Technically, the Tetris game is in html5/javascript based on an open-source Tetris by Choogmin Lee[1] and can be played within a web browser. It already featured a standard Tetris mode using a **7-bag** randomizer, a way to distribute pieces that mimics a bag in which one of each piece has been put and then distributed one after the other. This system is used to provide randomization while maintaining a balanced distribution between the 7 different type of pieces. We developed **notNice**, a variation in which the game stops providing the player with bar-shaped pieces when the player is ready to complete a 4-line, then provides two bars consecutively once a 4-line is no longer possible. All other aspects are identical to the 7-bag variation. Then, we developed **covExplore**, inspired by the Covid-19 crisis and the complexity of dealing with propagation while maintaining an activity (here stacking pieces). Some blocks of the pieces are colored in green and can infect neighboring blocks. Most of them will heal, become immune and take a blue color. Some others will become very sick (colored in red), a few of them will die and disappear from the game board, leaving a gap.

We implemented a logging system. When a piece appears, an AJAX query is sent to a PHP page to save all the logs of the previous episode; player's actions and game state variables such as the game board data. This information is serialised for the AJAX query and saved in a MySQL database.

4 Method

Our sample was of 31 persons, 22 who identified as women, 9 as men. They were between 20 and 57 years old (avg: 30, std deviation of approx. 10.5). The observations took place over 4 days at two different French universities. Participants were voluntary students, teachers, researchers and administrative staff. The entire protocol consisted of a questionnaire comprising steps in which the participants had to play the different variations of Tetris and answer questions

[1] https://github.com/clee704/tetris-html5.

after each run about the changes they perceived. Direct observations of their playstyle were made and most of the participants were interviewed after. For this study, we used primarily data from the game logs and some observations to facilitate the cluster interpretation. For each variation, the player is allowed to play as many times as they wish. In total, 110 runs were analysed (standard 7-bag: 35, notNice: 38, covExplore: 37). Three runs have been excluded because the game logging did not work properly on them.

In order to identify different playstyles, we decided to use Principal Component Analysis or PCA, a method for data analysis which transforms a set of linked variables into a smaller set. We first cleaned and treated the game logs using the R language. We aggregated the data per runs and computed variables usually used in Tetris game stats such as keys per pieces.

As we are interested in playstyles and not winning strategies, the indicators regarding inputs and strategy were divided by the number of episodes, lines or inputs (depending on the variable) giving us a frequency. This made sure the duration or number of pieces played in each run would not impact the results. The quantitative variables selected can be classified in different categories:

- **Game board**: minimum and maximum height, total number of gaps, height mean absolute deviation
- **Inputs**: left and right shifts, left and right rotations, soft and hard drops, keys pressed per pieces (KPP), keys pressed per second (KPS), missed inputs (when a key is pressed that is not part of the controls)
- **Strategy**: number of combos (combos: succession of episodes with lines completed), number of 4-line, number of 4-line per pieces, number of B2B (back-to-back: two 4-line in a row)
- **Scoring**: pieces dropped per second (PPS), gravity (piece descend speed), maximum level, final score and number of lines
- Time delay between a piece apparition and the first input

The qualitative variables used to explain the clusters are the player's id, the run number, which variation is played and how the run ended (player quit the run, timer ended or game over).

We visualised the results using the R-package Factoshiny[2]. It reduces the variables by itself and allowed us to manipulate the data in order to understand it better. This package also automatically edits a report with the different clusters highlighted with the PCA.

5 Results

Using the PCA method is useful to reduce the dimensionality of several quantitative data while capturing the greatest amount of variance in the data. We can then discover and define clusters in the dimensions PCA highlighted. Clusters

[2] http://factominer.free.fr/graphs/factoshiny.html.

can be characterised because they differ from the average. We will thus first present an average run of our sample and then describe the different playstyles.

In an average run of our sample, the board has a mean minimum height of 4.04 blocks and a mean maximum height of 8.80 blocks with a height mean absolute deviation of 1.80 block. Knowing that the game board has a height of 20 blocks, it implies that the game board stays mainly below the middle. This run would also have an average of 9.91 gaps left in the game board (means of gaps present per episode). The mean time delay between the apparition of the piece and the first input would be of approximately 1.03 second. The mean inputs frequency is an average of 1.41 key per second and approximately 5.66 inputs for landing a piece. 0.26 piece are placed per second (around a piece every 3.85 seconds). The average run has a score of 5395 points. With median analysis, an average run would total no 4-line but a combo every 10 lines in average. With input frequency analysis, we know that a little more than half of the inputs are left and right shifts.

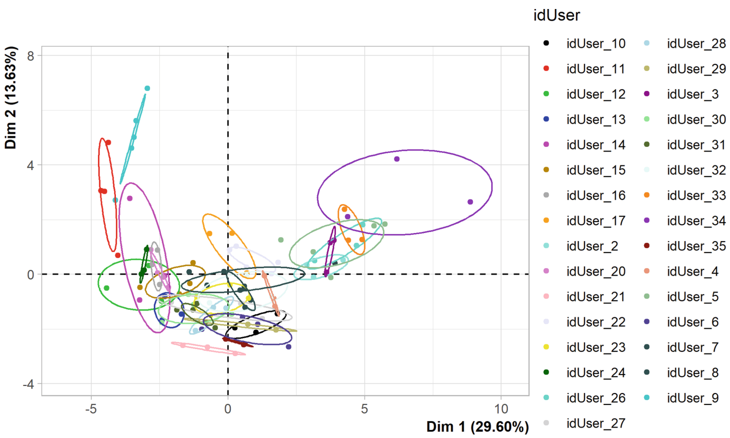

Fig. 2. Individuals factor map created using Factoshiny. One color per individual. (Color figure online)

The first two dimensions of the analysis express 43.23% of the total dataset variance. This value is strongly greater than the reference value of 16.23%[3] and the variability explained by this plane is thus highly significant. We studied the first 6 dimensions of the PCA with a cumulative percentage of variance of 76.26%. Each dimension defines two or three clusters that we will present. Since the data is related to runs, the clusters qualify runs and not players directly. However, the Wilks test p-value reveals that for each dimension, the variable factors are best separated on the plane by player's id (see Fig. 2 for a graphic visualisation). It is therefore acceptable to infer that each Tetris player has their

[3] Reference value: the 0.95-quantile of the variance percentages distribution obtained by simulating 9000 data tables of equivalent size on the basis of a normal distribution.

	Characteristics	High values	Low values
1	Gaps left, high KPP, few lines	Soft drops, KPP, gaps, left rotation, missed inputs, KPS, max. height, height mean absolute deviation	Right rotation, lines, left shift, right shift, level, score, combos
2	Slow play, very few gaps, low game	Soft drops, time delays, KPP, lines	Max. height, min. height, gaps, PPS, KPS, hard drops
3	Fast, meaningful inputs, clean, low game, use of 4-line	PPS, score, max. level, KPS, hard drops, 4-line per pieces, 4-line, gravity, lines	Time delay, soft drops, min. height, gaps, max. height, KPP
4	Fast, lots of gaps left, high game	Min. height, max. height, gaps, hard drop, KPS, PPS, left shift	Soft drop, time delay
5	Voluntary defeats	Height mean absolute deviation, PPS	Left shift, right shift, lines, KPP, KPS, hard drops
6	Voluntary defeats after some time	Hard drops, height mean absolute deviation, PPS, KPS	Lines, 4-line, 4-line per piece
7	4-lines strategy	B2B, 4-line per piece, 4-line, gravity, score, level	Time delay
8	Left rotation	Left rotation, gravity, score, level	Time delay
9	Shifts and low game	Right shift, KPP, left shift, missed inputs	Max. height, combos, min. height, level

Fig. 3. 9 clusters highlighted through PCA, variables sorted from strongest to weakest.

own playstyle. This same Wilks test shows that the different variations and the run number do not seem to have a significant impact on the clusters. We decided that a cluster can be qualified as a playstyle if the data is collected from someone who plays already knowing the mechanics. Therefore if one discovers the game, it cannot be qualified as a playstyle. Similarly, if one loses on purpose, it is not a playstyle because the person did not “play”.

The observations we made during the experiment allowed us to know that the first cluster (8 runs, 2 players) contains two participants who never played Tetris before and had no idea what the aim of the game was. The second (7 runs, 4 players), third (6 runs, 4 players) and fourth (4 runs, 2 players) clusters have the potential to be qualified as playstyles because they indicate ways of using the inputs and managing the board. The fifth cluster (2 runs, 1 player) consists only of two runs from a person who did not play at all for their second and third runs. They made the pieces go straight down until they lost. We find these runs again in the sixth cluster (5 runs, 4 players), along with other runs ended prematurely by the player after some time. The seventh cluster (4 runs, 3 players) is 4-line oriented and could also qualify as a playstyle. The two last clusters show the limits of our method. The eighth cluster (2 runs, 1 player) was created for one person who used exclusively the left rotation. The last cluster (3 runs, 3 players) is representative of several runs but the variables do not seem explicit enough to sketch a playstyle. The Fig. 3 sums up the different clusters found with the PCA.

6 Discussion and Limitations

In this study, four of the clusters can be qualified as playstyles: cluster 2, 3, 4, 7. Cluster 2 describes a slow and precise way of playing with a tendency to clean the game field. Cluster 3 encompasses people who played fast with a few inputs for each pieces, left little to no gaps and made 4-line. Cluster 4 includes runs where people played fast but with a high board containing gaps. Finally, cluster 7 encompasses runs where 4-lines were picked in priority.

Even if the majority of clusters makes sense with our direct observation, they do not all translate into a playstyle. If it is interesting that the clustering did capture new players (cluster 1) and players voluntarily loosing their run (clusters 5 and 6), we need more data to deepen the analysis. For instance, a few players used both hands on the keyboard making them use the inputs differently, but they do not appear as their own category. Most of them would also have preferred to play with a game controller as it was their usual way of playing. Forcing them to use a keyboard may have had an effect on how they approached the game.

Aggregating the data into runs mean that we miss precise moments during the game. Players may change strategy depending on the height of the game or react to certain pieces for example. Defining those moments and analysing how players change their behavior or not would be of interest to better understand different playstyles. Another area of improvement is the board analysis as seen in the work of Lindstedt and Grey. We have the data for the board and intend to add those data to later works. Our sample size is too small to generalise the playstyles we found and we only got 3 players scoring 4-lines. Finally, if we found different non-competitive playstyles, the PCA was not able to capture very unusual playstyles such as the participant trying to draw a dog on the board. We may need to use a top-down approach for such case.

Even if we found that few players showed different playstyles for different runs, those were not linked to the variations played. This may be explained by the limited amount of runs played for each variations. In a later study, we need to make them play more runs to see if players identify the changes and adapt their playstyle after a few runs are played.

7 Conclusion

If challenge and strategies to win are very important topics of video game design and development, they cannot encompass the diversity of playstyles found in video games as they tend to exclude from their analysis playstyles not oriented toward winning. Indeed, those profiles tend to be grouped into a broad category of novice players. However, players often give themselves different goals than the one given by the game and those are not well reflected in current studies.

In this paper, we showed that Principal Component Analysis on variables extracted from game logs could return relevant clusters of playstyles. This is still a work-in-progress research: the 4 playstyles we found will need more work to be demonstrated and we should find new ones in the future. However, the general approach and those first results are encouraging. In order to explore to what extent the way players make sense of their experience is dependant on their playstyle, we now need to compare data from the questionnaires and interviews with the playstyles. But before that, we will recruit more participants to deepen and validate the modelling of Tetris playstyles beyond skill, score and competition.

References

1. Bartle, R.: Hearts, clubs, diamonds, spades: Players who suit muds. J. MUDs Res. **1**(1), 19 (1996)
2. Bialas, M., Tekofsky, S., Spronck, P.: Cultural influences on play style. In: 2014 IEEE Conference on Computational Intelligence and Games, Dortmund, Germany, pp. 1–7. IEEE, Aug 2014. https://doi.org/10.1109/CIG.2014.6932894, http://ieeexplore.ieee.org/document/6932894/
3. Drachen, A., Thurau, C., Sifa, R., Bauckhage, C.: A comparison of methods for player clustering via behavioral telemetry. arXiv preprint arXiv:1407.3950 (2014)
4. Karpinskyj, S., Zambetta, F., Cavedon, L.: Video game personalisation techniques: A comprehensive survey. Entertainment Comput. **5**(4), 211–218 (2014). https://doi.org/10.1016/j.entcom.2014.09.002, https://www.sciencedirect.com/science/article/pii/S1875952114000342
5. Lindstedt, J.K., Gray, W.D.: Distinguishing experts from novices by the Mind's Hand and Mind's Eye. Cognitive Psychol. **109**, 1–25 (2019). https://doi.org/10.1016/j.cogpsych.2018.11.003, https://linkinghub.elsevier.com/retrieve/pii/S0010028518300756
6. Lora, D., Sánchez-Ruiz, A.A., González-Calero, P.A., Gómez-Martín, M.A.: Dynamic Difficulty Adjustment in Tetris. In: Proceedings of the Twenty-Ninth International Florida Artificial Intelligence Research Society Conference (2015)
7. Mader, S., Natkin, S., Levieux, G.: How to analyse therapeutic games: the player/game/therapy model. In: Herrlich, M., Malaka, R., Masuch, M. (eds.) ICEC 2012. LNCS, vol. 7522, pp. 193–206. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-33542-6_17
8. Nacke, L.E., Bateman, C., Mandryk, R.L.: BrainHex: A neurobiological gamer typology survey. Entertainment Comput. **5**(1), 55–62 (2014)
9. Norouzzadeh Ravari, Y., Bakkes, S., Spronck, P.: Playing styles in StarCraft. In: European GAME-ON Conference on Simulation and AI in Computer Games (2018)
10. Spiel, K., Bertel, S., Kayali, F.: Not another Z piece!: Adaptive Difficulty in TETRIS. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, Denver Colorado USA, pp. 5126–5131. ACM (May 2017). https://doi.org/10.1145/3025453.3025721, https://dl.acm.org/doi/10.1145/3025453.3025721, zSCC: 0000013
11. Tekofsky, S., Spronck, P., Goudbeek, M., Plaat, A., van den Herik, J.: Past our prime: a study of age and play style development in Battlefield 3. IEEE Trans. Comput. Intell. AI in Games **7**(3), 292–303 (2015). https://doi.org/10.1109/TCIAIG.2015.2393433, http://ieeexplore.ieee.org/document/7012062/
12. Yee, N.: Motivations for play in online games. CyberPsychol. Behav. **9**(6), 772–775 (2006)