

Decision Making Styles as Deviation from Rational Action: A Super Mario Case Study

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Abstract

In this paper we describe a method of modeling play styles as deviations from approximations of game theoretically rational actions. These deviations are interpreted as containing information about player skill and player decision making style. We hypothesize that this information is useful for differentiating between players and for understanding why human player behavior is attributed intentionality which we argue is a prerequisite for believability. To investigate these hypotheses we describe an experiment comparing 400 games in the *Mario AI Benchmark* testbed, played by humans, with equivalent games played by an approximately game theoretically rationally playing AI agent. The player actions' deviations from the rational agent's actions are subjected to feature extraction, and the resulting features are used to cluster play sessions into expressions of different play styles. We discuss how these styles differ, and how believable agent behavior might be approached by using these styles as an outset for a planning agent. Finally, we discuss the implications of making assumptions about rational game play and the problematic aspects of inferring player intentions from behavior.

Introduction

Recent work in Game AI research has seen an increasing interest in the generation of believable bot behavior: bots that not only challenge or interest humans, but play like humans. For instance, the well known Mario AI Championship (Karakovskiy and Togelius 2012; Shaker, Togelius, and Yannakakis 2013) recently added a Turing Track to the competition and the 2K Botprize (Hingston 2013; 2010) has long been a successful recurring event. Both competitions challenge researchers and developers to create bot players whose behaviors are as indistinguishable from those of human players as possible.

At the core of the pursuit lies evidence that the experience of playing against another sentient player brings engagement and entertainment to most games (Togelius, Yannakakis, and Shaker 2012). The phenomenon that believable human-like interaction from a computer system will generally result in human emotional and behavioral reciprocation has been documented for many kinds of human-computer-interaction (Reeves and Nash 1997). Believability can be

construed as a question of being able to attribute intentionality to a bot through inferring from observation that it is exhibiting goal directed behavior and by interpreting and understanding this behavior. Dennett named this process of ascribing agency to an object from assumptions about beliefs and desires the “Intentional Stance” (Dennett 1987). In short, if we ascribe beliefs and desires to an artificial agent, we are likely to also ascribe to it intentions and from the intentionality comes the tendency toward treating the object as sentient.

Our hypothesis is that the way humans deviate from an optimal course of action in the game theoretical sense, whether due to lack of skill or the pursuit of goals not formalized in the game's rule structure, is useful in making behavior seem intentional. We further hypothesize that decisions are a useful way of operationalizing the deviations. We attempt such an operationalization by contextually analyzing the observable actions that humans take within the rule systems of games as collected in play traces.

Related Work

Modeling play styles is nothing new in general. Various signals from the player have been employed to enable differentiation between and grouping of players, ranging from facial expressions during game play (Asteriadis et al. 2012) over spatial exploration and behavior overall (Drachen, Canossa, and Yannakakis 2009; Asteriadis et al. 2012) to simply player performance in terms of score (Asteriadis et al. 2012).

Additionally, the psychological literature contains a cornucopia of models for describing how behavior is derived from or influenced by unobservable, latent traits. Below, we briefly visit and relate to previous work in generating human-like behavior from latent trait models and exemplify their application to play style modeling.

Latent Trait Models of Behavior

One approach for creating believable bots is to start out with general models of human cognition and motivation and use these models as generative systems for bot behavior. Cognitive psychology concerned with personality and motivation sees human behavior as the expression of latent tendencies inherent in the individual that are stable over time.

Personality models are generally concerned with preference and appraisal tendencies. They are typically con-

structured by examining people's preferences and appraisals in response to general questions or specific situations, real or imagined. There is evidence that such models can be used to explain play styles to a certain extent. For instance, personality has been shown to significantly influence behavior in on-line virtual worlds (Yee et al. 2011). Personality models rest on the idea of a cognitive-emotional system that responds to various situations in a predictable fashion because the system – barring any life-altering experiences such as physical or psychological trauma – is relatively stable over time. Personality models are accepted as having explanatory use and validity in cognitive psychology and have been used for generating believable bot behavior (Rosenthal and Congdon 2012). A similar, but less investigated and established latent model, is humans having decision making styles as traits. The general idea is analogue to that of personality profiles, but suggests that humans exhibit stable decision making biases. There is evidence that humans possess such stable and predictable decision making styles (Scott and Bruce 1995). The question then becomes how to recognize such decision making biases in game play.

Irrational Play

The idea that play is not purely rational, but is driven by multiple motivations aside from the wish to perform optimally within the strict rules of the game, is well known. For instance, *agon* is only one of Callois' classic categories (Callois 2001) of play and the idea has also been expressed in concepts such as a game-play continuum (Malaby 2007). In the same vein, research has attempted to capture the deviation from rational play by observing the interactions between players in multiplayer games (Smith 2006).

The Compliant-Constructive Continuum. It has been proposed that the discrepancy between the individual player's intentions, and the ones strictly afforded by the game rules, can be described as residing on a compliant-constructive play style continuum (Caspersen, Jespersen, and Pedersen 2006).

The completely compliant player only uses the rules of the game to respond to the affordances presented by the game, attempting to move closer to achieving the winning condition. An example would be a *Counter-Strike* (Valve 1999) player who directs all her play efforts toward making her own team win, disregarding any aesthetic preference in e.g. distance to enemies or weapon choice in order to optimize her contribution to her team's coordinated efforts.

The completely constructive player uses the game rules to enable intrinsically motivated actions and situations that may or may not be related to the winning conditions, and hence affordances, of the game. An example would be a player using the game world to enact a protest against violence through inaction or graffiti (Antunes and Leymarie 2010).

These two examples represent positions of play styles on opposite ends of the compliant-constructive continuum. Importantly, the *completely* compliant and rational play style can be thought of as apersonal and a matter of *solving* the game: From a given state in a deterministic game of perfect

information, the compliant-rationally best action(s) will be the same for any player. By extension, the style of a particular player should then be expected to be found in the part of the play actions that are constructive, rather than compliant, and thus suboptimal from a game theoretical perspective.

Taking previous work on play styles, latent traits, and rational play into consideration, the novelty of the approach described here lies in the understanding of play styles as *series of decisions leading to actions systematically deviating from game theoretically rational actions*.

Belief-Desire-Intention Agents

Key to investigating the usefulness of the analytical approach outlined above is having a clear mechanistic model of the process leading from intention to decision to action that can be reverse-inferred with some degree of precision from observed actions.

The artificial intelligence literature provides a well-known framework for describing and generating intentions and plans from beliefs and desires: The Belief-Desire-Intention (BDI) framework for agents (Rao and Georgeff 1997). The framework is originally generative, but this work aims to use the model analytically on empirical observations.

The use of BDI agents has a rather long history in simulations, but they have less commonly been found in computer games, the most notable examples perhaps being the *Black & White* series of god-games (Lionhead Studios, 2001, 2005) (Norling and Sonenberg 2004). The paradigm is fundamentally a reasoning and planning approach that uses three high level concepts, *beliefs*, *desires*, and *intentions*, that together constitute an agent model.

Beliefs describe the agent's current representation of its own state and the state of its surrounding environment.

Desires describe all the current goals that the agent would like to achieve at a given time.

Intention(s) describes the active goal(s) that the agent is pursuing at any given time.

In addition to this, a typical approach is for the agent to have a plan library, from which it selects courses of action to form intentions (Norling and Sonenberg 2004).

Two main aspects of the BDI paradigm make it especially useful for modeling human decision making: The psychological nature of the model maps well to a human introspective understanding of thought processes. Norling and Sonenberg (2004) mention that the framework does not match the actual way that human reasoning occurs, but by small appropriations, the BDI paradigm can fit the typical model of human reasoning from cognitive psychology: If beliefs are understood as a common headline for perception and evaluation of the state of an agent's internals as well as its environment it need not be a completely conscious representation. We can take the beliefs as being the total sum of the agent's available information, including declarative, non-declarative, procedural, and emotional knowledge. By the same reasoning, desires can be understood as motivations widely, incorporating both conscious wishes as well as unconscious drives, instincts and behavioral tendencies all

the way down to the conditioned level. Finally, intentions can be understood as the selection basis for the current plan under execution, regardless of whether this plan was motivated by conscious determination or by partially or wholly intuitive or procedural impulses. That means that the moment an intention is formed and followed, in the BDI framework, it can be understood as a decision.

Decision Making Styles In this work we attempt to use the BDI framework as a backdrop for understanding play traces from the Mario AI Benchmark (MAIB) testbed (Karakovskiy and Togelius 2012), assuming that the actions observed during game play are decisions that in turn are realizations of intentions. We further assume that any variation from the rationally optimal is grounded in intentions beyond the scope of the game rules, and a realization of the player’s play style as a personal trait¹, realized dynamically in interaction with the context of the game rules. As such, the complete chain of inference leads backwards from actions to decisions to intentions to beliefs and desires and cannot be understood without a deep understanding of the game’s rule structure. We do not necessarily assume that beliefs or desires are wholly conscious, and as such decisions may be based partly or wholly on procedural knowledge and evaluative processes at the subliminal level. This is especially relevant to the MAIB framework, since it is a real-time game where perceptual and motor skills are emphasized.

The key to the project outlined here then becomes the question of how to approximate how a rational agent with the perceptual and motor capabilities of a human player would act while playing MAIB. If we assume that the player is a rational agent, and that we know exactly what information about the game state the player has access to and is able to perceive, the decision space of the game player narrows significantly, and we start becoming able to use combinations of normative and descriptive game theory to approximate what a perfectly playing rational agent would have done. In the following, we treat some of the general challenges to consider in collecting data on decision making from human players and proceed to examine an attempt at handling these challenges in a data set play traces from the MAIB.

Decision Making in the MAIB

The MAIB testbed is a well established framework for working with procedural content generation, player modeling, agent development and testing, and human imitation in platform games. It is a replication of the game mechanics and content of the classic 2D platform game Super Mario Brothers. The testbed has the advantage of being immediately familiar to most players in terms of content and mechanics. This may offset learning effects in experimental conditions and eases the administration of instructions during experimental runs. The game has simple keyboard inputs consist-

ing of buttons mapped to six different actions: *Down*, *Jump*, *Left*, *Right*, *Speed*, and *Up*.

The MAIB testbed offers several features that are of interest to the study of decision making in games. Because the game is played in a real-time (25 fps) simulation with an experientially continuous deterministic world with predictable physics, it offers a well suited backdrop for studying ecological decision making under well-known conditions. The testbed allows for a practically infinite number of unique positions and action sequences, ensuring that any two sessions played by humans are unlikely to ever be identical. Though the game world offers an impressive expressive richness vis-à-vis its limited reality, the game rules superimposed on top of the game world that the player is afforded to comply with are simple: Players should win levels as quickly as possible, while avoiding or killing enemies in their way, and collecting as many items as possible.

At every given moment during the course of a play through, only a subset of the level is visible to the player, providing no more information than can be assimilated at any given moment by a perceptually and cognitively normally functioning individual. The game presents most *relevant* information about the game state at any given time and can, as such, be considered a game rich in information (though not perfect, as blocks may contain various hidden power-ups and enemies can be hidden from sight for varying amounts of time).

Together these features allow us to construct an agent that plays the game as a completely rational, compliant human player would: By searching through the possible game states from any given position and finding the temporal path that best fulfills the above outlined affordances. One well-performing method for constructing such an agent has been provided by Baumgarten in previous work (Champan-dard 2009; Togelius, Karakovskiy, and Baumgarten 2010; Baumgarten 2013) in the form of a MAIB playing A*-agent. This agent was used to approximate the actions of a perfectly compliant, rational player during data collection².

Method

The following method was developed for discovering player decision making styles from actions performed in the MAIB testbed: Human subjects are asked to play randomly generated levels in the MAIB. All human actions are logged and from these a play trace is constructed, representing their path through each particular level. An A*-agent solves each level using a set of affordances determining what possible actions are given priority and to which extent, and a corresponding trace is constructed. In this particular case the only affordances are to complete the level as quickly and safely as possible. The difference between the two is determined by comparing the maximal Y values of the human and the agent traces for each tile in the level resulting in a deviation

¹Considering the source of the play style tendency as a trait is beyond the scope of this work, but as noted in the section on related work, decision making style, cognitive and personality models may be of use here.

²As the A*-algorithm itself is well known, we refer to Baumgarten’s work (Champan-dard 2009; Togelius, Karakovskiy, and Baumgarten 2010; Baumgarten 2013) for methods of appropriating the algorithm to the MAIB testbed. His description and code formed the basis for the implementation used for this study.

trace. Additionally, an action deviation matrix is computed between the normalized action frequencies of the player and the normalized action frequencies of the agent. Features are then extracted from the deviation trace, while the normalized input differences for each session are used directly. The set of observations is subjected to cluster analysis to discover play styles across individuals and their play sessions. The prevalence of clusters for each individual is correlated with measures of player skill as an indication of the relation between the human play style and the agent play style. Features are compared across clusters to determine how and to which degree clusters exhibit different play styles. Finally, the original traces of the discovered play style clusters are visualized on selected levels for interpretation.

Feature Extraction and Clustering

The following features are extracted from the deviation trace for every play through: The mean (*Mean*) of the deviation trace in order to represent the player's average deviation from the agent trace. The maximum deviation (*Max*) from the agent trace, in order to capture actions extremely different from the agent trace. The standard deviation of the deviation trace (*Sd*) in order to represent the variation of the deviation trace. The means of the first and second differences of the deviation trace (*Diff1*) and (*Diff2*), representing local variation in the deviation trace, i.e. the tendency of the player to move vertically in the level in a manner different from the agent's.

The action frequencies (*Down*, *Jump*, *Left*, *Right*, *Speed*, *Up*) of each player/the agent across the play through of the level are captured as control inputs from each frame of the game. The frequencies are normalized to a range of 0 to 1, relative to the number of frames from start to finish in the play session. The difference matrix is then calculated as the absolute value of the difference for each input type. In order to avoid any direct convolution of skill with play style, no measures of score or performance are used as features.

The total feature set is used as input for an agglomerative hierarchical clustering process, applying Ward's minimum variance method (Kaufman and Rousseeuw 2005).

Data Collection

A data set was generated from 10 human players playing 40 different, short levels of the MAIB testbed, yielding a total of 400 play sessions. All player inputs were recorded and re-played to generate a trace of the players' routes through the levels. The levels were of varying difficulty, but all were exactly 100 tiles long. On average players completed levels on approximately 35% of the play throughs, though substantial individual differences were observed (range 0-70%, std.dev. 24.7). For each human play through a deviation trace and an action deviation matrix were calculated as described above.

Results

The clustering yielded 4 well defined clusters (*C1*, *C2*, *C3*, and *C4*) depicted in Fig. 1. The selected cluster for each session was mapped back onto its player, yielding 10 observations with cluster membership frequencies for each player,

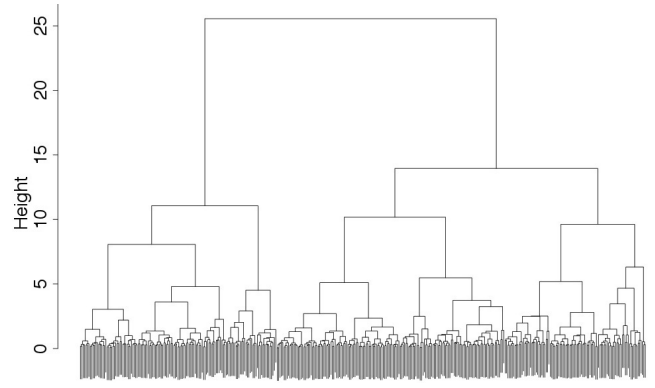


Figure 1: Dendrogram from the agglomerative hierarchical clustering of the extracted features from 400 observations. The tree was cut at the level of four clusters.

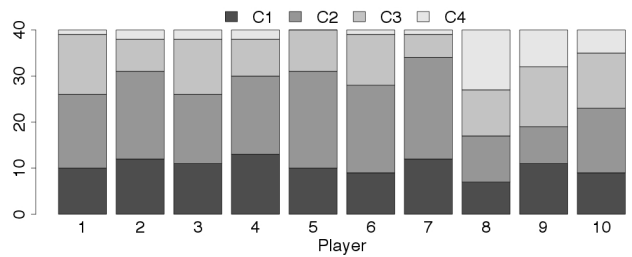


Figure 2: Players' individual cluster expressions across all play throughs. Each column represents a player and each shading within each column represents how many of the individual player's 40 play sessions were grouped into clusters *C1*, *C2*, *C3*, and *C4* respectively.

depicted in Fig. 2. Additionally, each player's average score and average win rate across all sessions were added to the dataset as indications of player performance. A correlation analysis was conducted in order to investigate the relationship between deviation style predominance and in-game performance. The results are reported in Table 1 and indicate that the two play styles *C1* and *C2* are correlated positively with performance while play styles *C3* and *C4* are correlated negatively with performance. They also indicate that *C2* is characterized by a *Jump* frequency close to that of the agent, while *C4* is characterized by a *Jump* frequency different from the agent's, and that *C1* and *C2* have *Speed* frequencies closer to the agent's in contrast to *C3* and *C4*.

A mapping of play style clusters to levels was conducted, showing how often a given play style was expressed on each particular level. The frequencies of the results were used to identify levels that allow for the expression of all clusters identified across the dataset. The results are presented in Fig. 3 and indicate that most levels only enable the expression of some play styles.

To further investigate the differences between the clusters across the features, the centrality of each cluster with respect to each feature was established using the Hodges-Lehmann Estimator of Location. To test for significant group differ-

Feature	Wins	Score	C1	C2	C3	C4
Mean	-0.06	-0.06	-0.04	-0.05	0.07	0.02
Max	0.15	0.16	0.04	0.17	-0.03	-0.21
Diff1	-0.09	-0.10	-0.06	-0.11	0.06	0.09
Diff2	-0.01	-0.03	-0.01	-0.01	-0.09	0.06
Down	-0.06	-0.06	-0.07	-0.03	0.07	0.00
Jump	-0.33	-0.33	-0.09	-0.35	0.02	0.44
Left	0.08	0.09	0.06	0.14	-0.12	-0.05
Right	-0.13	-0.10	-0.02	-0.03	0.01	0.07
Speed	-0.69	-0.68	-0.46	-0.67	0.72	0.39
Up	-0.06	-0.08	-0.08	-0.05	0.09	-0.00
C1	0.57	0.59	-	0.37	-0.46	-0.16
C2	0.86	0.85	-	-	-0.72	-0.85
C3	-0.66	-0.62	-	-	-	0.27
C4	-0.73	-0.75	-	-	-	-

Table 1: Spearman correlation between cluster membership frequency, features, and performance measures. Values significant at the $p < 0.05$ level are in **bold**. Significance values are subjected to Holm-Bonferroni correction for multiple tests.

Feature	C1	C2	C3	C4	H	df	Sig.
Mean	1.96	1.73	2.88	1.54	174.0	3	0.00
Max	6.00	7.50	7.50	4.50	309.3	3	0.00
Sd	1.70	1.91	2.22	1.43	152.4	3	0.00
Diff1	0.10	0.10	0.17	0.09	26.5	3	0.00
Diff2	-0.00	-0.04	-0.02	0.00	3.1	3	0.38
Down	0.00	0.00	0.00	0.00	5.8	3	0.12
Jump	0.08	0.08	0.09	0.23	15.8	3	0.00
Left	0.04	0.03	0.04	0.03	5.9	3	0.12
Right	0.44	0.34	0.38	0.42	25.7	3	0.00
Speed	0.60	0.53	0.78	0.91	16.2	3	0.00
Up	0.00	0.00	0.00	0.00	9.8	3	0.02

Table 2: Kruskal-Wallis H tests for differences between clusters. *C1-C4* contains the Hodges-Lehmann Estimator of Location (Lehmann and D’Abrera 1975), as a measure of centrality, for each cluster for each feature to allow for comparison. Note that for some features, e.g. *Speed*, all clusters are differ from one another, while for others, e.g. *Jump*, one cluster deviates.

ences, each feature was subjected to a Kruskal-Wallis analysis of variance (Lehmann and D’Abrera 1975). The results are reported in Table 2 and indicate that most features significantly differ across groups, with the exception of *Diff2*, *Down* and *Left*. Overall, *C4* resembles the agent the most as expressed by the mean trace difference. Examining the correlation between *C4* and and performance measures, it seems plausible that *C4* resembles the agent because this play style dies early, but acts like the agent in the early stages of the level before dying. This interpretation is supported by the fact that the *Jump* and *Speed* frequencies of *C4* are very different from the agent’s, while the *Jump* and *Speed* frequencies of the high-performing *C2* cluster are closer to those of the agent.

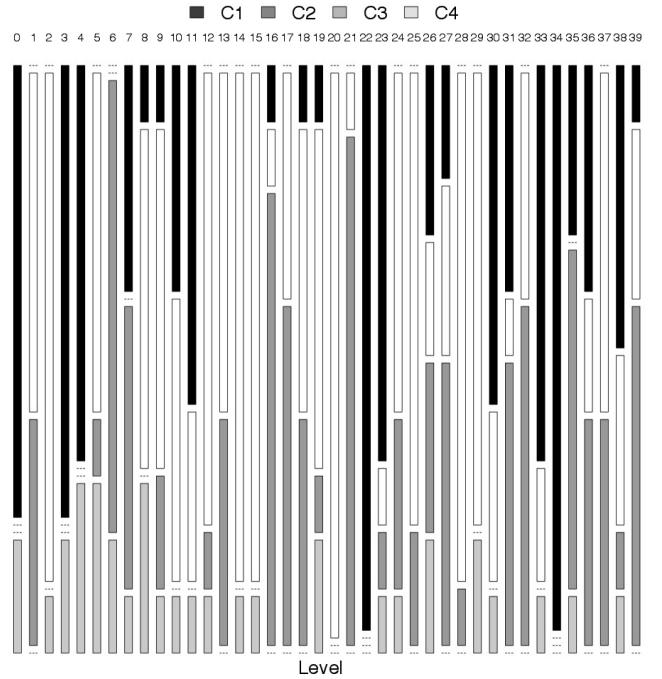


Figure 3: Expressed play style clusters mapped to levels. Each shading represents a cluster.

For exemplification, three levels enabling all play styles were selected and visualized in Fig. 4. These graphs indicate that *C2* traces resemble agent traces. So do *C4* traces, but only for a short period of time before losing, cutting the session short. The graphs show *C1* and *C3* diverging from the agent in terms of trace path, with varying performance. In terms of the compliant-constructive continuum relative to the A*-agent, we suggest that *C2* and *C4* could be considered compliant and skilled/unskilled respectively, while *C1* and *C3* are acting more constructively and less stably. This interpretation, of course, only holds to the extent that one accepts the A*-agent as a relevant proxy for a rational, compliant, skilled MAIB player.

Discussion

The results presented in this paper reveal a number of insights about the play styles of the participants. The clustering of the play styles and the correlations to performance measures indicate that the applied approach might indeed be able to differentiate between different kind of play styles, and by extension that the operationalization of decision making styles into deviation from rational behavior is applicable for a game of the scope of the MAIB. Further work should be undertaken, however, to investigate and control for the influence of the particular level as Fig. 3 suggests that such an influence is present.

Also, multiple theoretical assumptions still stand unresolved. It is unclear from the results presented here to which extent the assumptions of what constitutes rational behavior are indeed appropriate and how this approach would transfer to games of higher complexity than the MAIB. The A*-

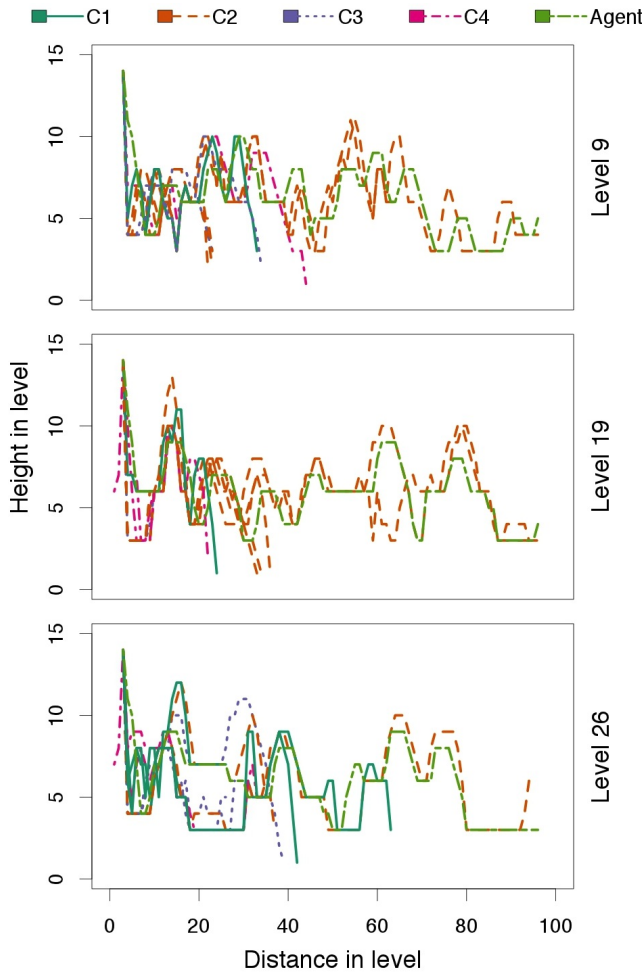


Figure 4: Traces from three levels. Each graph represents a trace of an individual player or the agent. Note that the high-performing C2 traces bear resemblance to the agent traces.

agent is arguably a high-performing solution for the MAIB, but different agents might perform equally well. With more than one normative game theoretical solving approach to the game, it becomes difficult to prescribe one over the other as a perfect baseline. From a pragmatic perspective any high-performing solution might be good enough, as long as it serves as a baseline by which to differentiate players, but it is an assumption that warrants further research. One approach to this problem could be the construction of multiple baseline agents and characterizing players in terms of which baseline agent they resemble the most or the least — generating procedural personas.

A first step for future work should be to include longer and more varied levels, allowing for a greater expressive range in the play throughs. This would also force an elaboration of the assumptions of what rational behavior in the MAIB is, and would necessitate a hierarchy of affordances or a similar method for identifying the most plausible intentions of the player from multiple options. Should the agent prefer enemy kills over bonus items or vice versa? In the scope of the

current study, this consideration is not necessary, as the only affordances are reaching the end of the level as quickly and safely as possible. While this limited scope benefits this first tentative exploration of the approach, more complex game situations will be needed to push the boundaries of decision style identification from deviations from rational play. In the same vein it is clear that any decision styles extracted from player behavior will be dependent on the game in question and that the extent to which decision making styles generalize between games remains unknown. If decision making styles in games are stable traits expressed across situations, this should be detectable across different games, but it remains to be seen if the contexts drown out any signal of the individual player’s decision making style. A comparative study of multiple games, preferably using the same sample of players, would be necessary.

Also remaining is the answer to the question of how to use the clusters identified as decision making styles for synthesizing behavior in the BDI framework. The extension of this method to a multiple-agent approach would enable this, if each agent was characterized (even if not strictly implemented) in the BDI framework, exhibiting different desire hierarchies and different plans for achieving these desires. This could be achieved by using a battery of different agents or by constructing an agent with dynamic affordance-response preferences that could be weighted between or during play-throughs.

Finally, the difference trace used in this limited study is created with reference to an agent completing the whole level. A more precise approach might be for the agent to determine its preferred action for each frame of the player’s play session, yielding a difference trace based on moment-by-moment differences instead of session-based differences.

Conclusion

We have presented a framework for characterizing player behavior in terms of deviations from rational actions. We believe this framework could be used as a foundation to further understanding of player behavior, which is often analyzed in a rather ad-hoc way using unsupervised learning. This framework was demonstrated using an analysis of play styles in the Mario AI Benchmark, with a high-performing A*-based agent providing the ground against which human play traces were contrasted. This analysis yielded features that allowed players to cluster meaningfully with significant differences between them. These clusters were also found to correlate with playing performance. The current work provides ample opportunity for further investigation.

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