Between Intention and Improvisation: Limits of Gameplay Metrics Analysis and Phenomenological Debugging

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ABSTRACT

Gathering gameplay metrics and analyzing this data to make sense of player behaviour has become a widespread practice both in game development studios and academic circles. The practice implicitly reproduces a clear neopositivistic assumption: player motivations, desires, beliefs and personality are encoded in the player behaviour and it is sufficient to interpret metrics data to unravel all sorts of information about the player. This unspoken paradigm does not take into account a fundamental difference in the nature of actions undertaken by players. In fact player behaviour is not homogeneous nor is all to be considered a conscious or unconscious expression of personality or intention. Even if, admittedly, the actions of a player are initially completely intentional (i.e. flanking an enemy to surprise her) there are a number of factors (i.e. exiting cover by mistake and being surprised while flanking) that could turn that initial intentional behaviour into an improvised sequence of actions (i.e. erratic flight or discomposed shooting). Gameplay metrics analysis tends to assume that all player behaviour is equivalent and it is generally treated undistinguishedly as expression of player intentions; what is argued in this article are the benefits of acknowledging the different natures of intentional and improvised player behaviours.

Phenomenological debugging is the practice through which game developers attempt to elicit defined emotional responses. Although it is not believed that it is possible to discover deterministic correspondences between certain stimuli and defined emotional responses, it is still possible to build scaffolds for certain desired experiences. Awareness of the shift between intentional actions and improvised actions becomes fundamental during this process of phenomenological debugging. A framework for identifying the

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shift between different behaviours is also proposed based on mixed method blending both qualitative observations and quantitative analysis.

Keywords
Gameplay Metrics, Datamining, Planned Behaviour, Intention, Improvisation, Motivation, Phenomenological Debugging, Theory of Reasoned Actions, Theory of Planned Behaviour.

INTRODUCTION
Collecting and analyzing telemetry data is becoming a standard practice in both game development and academic circles. This data is routinely used to create player profiles and models for a variety of purposes. Until now all data related to player behaviour has been dealt with indistinctly, as if it represented manifestation of players' will and intention. This paper proposes a framework to differentiate between different classes of actions that players can perform in games, problematising the practice of building player models out of actions that only in some instances can be said to be completely intentional and consciously decided.

Game Telemetry and Gameplay Metrics:
Telemetry is defined as a system that allows remote collection, storage, measurement, analysis and reporting of information. Game telemetry specifically refers to the automated collection of game metrics, namely instrumentation data about a) the performance of the game hardware, b) measures about the development and production processes, and c) measures of how players interact with the game (Mellon, 2009). It is this last category, gameplay metrics, which has attracted most interest both from game industry and academic researchers. Analyzing gameplay metrics can benefit several aspects of game development: user research, game and level design, community services and marketing.

Metrics and user research:
Metrics analysis has been supplementing existing methods of player research, both usability testing (measuring ease of operation of the game) and playability testing (exploring if players have a good experience playing the game), by offering insights into how people are actually playing the games under examination (Thompson, 2007; Kim et al., 2008). Canossa et al. (Canossa et al., 2011) have shown how triangulating quantitative and qualitative angles can overcome limitations imposed by exclusively quantitative approaches.

Metrics and design:
Metrics analysis has also had deep effects on both game and level design practices. Mellon (Mellon, 2004) presented data from automated testing of MMOG development and operations in The Sims Online. Microsoft Game Labs performed extensive user testing of Halo 3, generating metrics-based analyses of player progression and heatmaps (Thompson, 2007; Kim et al., 2008). Canossa and Drachen have employed gameplay metrics from Tomb Raider: Underworld and Kane & Lynch: Fragile Alliance to present aggregate statistics and visualizations. These analyses have been instrumental in fine tuning level design and balancing game mechanics (Drachen and Canossa, 2009a; Drachen and Canossa, 2009b; Drachen and Canossa, 2011).

Metrics and player communities:
Game studios have employed statistics about players' behaviour to build communities for a long time now: Valve was among the first to make available to their community highly aggregated data about player behaviour (Steam Games Statistics). Bungie took it a step further by not only providing aggregate statistics about large number of players, but also presenting each player with personalized reports (Bungie Games Statistics). A number of companies have also emerged to provide game studios with services aimed at building, from the ground up, on-line gaming communities by leveraging gamer profiles, achievements, scoreboards, game replays and statistics (Agora Games).

Metrics and marketing:
There have also been considerable efforts to monetize this kind of intelligence: spearheaded by Zynga, a number of developers have included dashboards in their games that allow rapid A/B testing, leading to marketing-driven development models (Pincus and Gordon, 2009). Even traditional developers such as EA are investigating ways to monetize gameplay metrics intelligence and are actively researching into player retention for their sport franchises (Weber et al., 2011).

Metrics and academia:
Furthermore, the datasets generated while harvesting gameplay metrics have already been successfully employed by academic researchers to experiment with innovative analytical techniques (Thurau and Bauckhage, 2010).

GAMEPLAY METRICS AND PLAYER MODELING

In general, metrical data analysis is useful to compare the intent of the designers with the actual behavior of the players and to assist developers with quantifying their vision into elements that can be measured (Drachen and Canossa, 2009a). Even if it is impossible to assess reasons and motivations behind players' actions just by looking at their in-game behaviour, analysts still rely heavily on game metrics to evaluate user behavior. A rather common approach to evaluate user behaviour seems to be player profiling or player modeling. As expressed by Smith et al. "player modeling is a loose concept. It can equally apply to everything from a predictive model of player actions resulting from machine learning to a designer's description of a player's expected reactions in response to some piece of game content"(Smith et al., 2011a; Smith et al., 2011b). Houlette first described models of individual players that are created by monitoring gameplay metrics (Houlette, 2003). Charles and Black added explicit interrogation of players to the metrics-based inductive approach described by Houlette (Charles and Black, 2004). In both previous cases, the player models are generated for greater and better adaptation of game system or shaping bot behaviour (forward simulation and prediction of moves). On the other hand there is also a wealth of research on player models to imply players during design (Canossa, 2009; Schell, 2008). Game designers often form non-explicit, internal models of players from a mixture of observation and accumulated design experience. These models have a considerable impact on level design, game design and production of the game, influencing the gameplay experience at a far deeper level than any adaptive game system. Computational models have been created to verify designers' models and assumptions and have proved invaluable tools (Drachen et al., 2009) also with the purpose of predicting player behaviour (Mahlman et al., 2010). In general it seems to be possible to assert that player models help the process of interpreting or predicting actions and behaviours observed in players, independently whether they are physical individuals, bots or implied instances of hypothetical behaviours. Player models are sense-making lenses that allow the extraction of meaning from behaviours in games.

PROBLEMATISING METRICS ANALYSIS AND PLAYER MODELING

It has been demonstrated until now how widespread are the practices of analyzing gameplay metrics and creating player models with the purpose of understanding, predicting or replicating player behaviour. Game industry and academic circles alike are focusing their efforts in this direction because of the many benefits provided by these approaches: objective, quantifiable data, actionable information, concrete cues for iterating design. Several other domains share such a focus on human behaviour: marketing, advertising, health care, public relations and human computer interaction just to name a few. In these fields a special attention is given to planned behaviours and reasoned actions, particularly attempting to predict behaviours by evaluating the intention behind certain behaviours. The leading theories behind this work are Fishbein and Ajzen's Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980) and its modified version in 1991—Theory of Planned Behaviour (TPB) (Ajzen, 1991). Thinking about intention and intentional actions implicitly acknowledges the existence of non-intentional actions. In philosophy, beginning with Jeremy Bentham intentionality was introduced for the purpose of distinguishing acts that are volitional and acts that are not. Husserl later posited that consciousness always implies intentionality and it is necessarily directed upon an object. This consideration assumes an ontological difference between volitional and non-volitional acts. Current practices of gameplay metrics analysis and player modelling are all based on the assumption that it is of no interest differentiating between volitional and non-volitional acts; this paper proposes a classification of possible player actions based on TPB.

Classes of player actions:

In the game Tomb Raider Underworld (Eidos Interactive, 2008) a player advancing along a narrow platform spots a tiger. Quite quickly she formulates the plan to dispose of the tiger with guns. After a couple of shots, without having even wounded the tiger, the player runs out of ammunition. Instinctively the player dodges the tiger's attack and jumps on a nearby ledge but, being slightly too distant, barely grabs the edge; at this point, after a burst of button-mashing on the controller, the player manages to hoist herself upon the ledge and evades the encounter, progressing in the game. What was clearly a well formulated, planned action turned into more and more chaotic behaviour, still achieving to progress towards the end goal. Not all player behaviour has the same weight and it should not always be treated as a conscious expression of players' will or intention. Not all actions from players are volitional and, as they are not necessarily an emanation of player intention or personality, they should not contribute in the same measure in creating descriptive or predictive models. As already asserted by Husserl, consciousness implies intention, hence non-intentional or partially-intentional acts can be said to be less aware. It is possible then to plot players' actions along a hypothetical intention/awareness axis.

Intentional Behaviours (IB)

The initial plan to shoot the tiger, being intentional, completely conscious, highly composed and planned, is the most aware act and can be addressed as Intended Behaviour (IB). The overarching goal is not to kill the tiger, but to advance progressing in the level. All clearly formulated, conscious actions fall in this class. Since “no plan survives contact with the enemy”, a clearly-stated intended outcome of the plan (the goal) will facilitate the process for the player to ad-lib her way to success when the detailed plans fall apart or where no detailed plans are available (absence of IB). IBs are explained particularly well by Theory of Reasoned Action and Theory of Planned Behaviour.

Trained Behaviours (TB)

The secondary action, dodging the tiger and jumping on the ledge, emerged as an automatic response out of an array of Trained Behaviours that the player has learnt during previous play sessions, they will be addressed as Trained Behaviour (TB). These TB are patterns that players build also across different games: for example “strafing” or “duck into cover” or “cover your back” could be patterns learnt in other games and might be activated almost instinctively by the total or partial failure of IB. Any automatic fallback response triggered without planning and mostly focused on execution will fall in this category. These patterns emerge from training, repetitions of the actions in order to learn them and increase performance skill. For example in team sports players spend a long time practicing strategies and building automatisms. Jazz musicians jamming together rely on a shared repertoire of patterns that they practiced individually. Soldiers as well are trained extensively to build automatic responses to situations, minimizing as much as possible the composition phase and focusing exclusively on execution; climbing the chain of command there are incrementally more resources devoted to composition. The library of trained behaviours contains both patterns learnt in other game experiences and also patterns that have been trained in the particular game at hand, meaning that game designers can operate a bias on what behaviours are preferable because the game prepares players to automatically respond in a certain way, in the absence of clear IB; at the same time each player’s history still contributes in shaping the end behaviour.

Chaotic Behaviours (CB)

The third class of actions, the button-mashing, was triggered by the player’s panic reaction facing a possibly fatal situation, namely falling in the abyss; these actions will be addresses as Chaotic Behavior (CB). Panic responses in case of difficult situations, chaotic improvisation without a clear goal, random behaviours to try out possible affordances, are all examples of CB. These behaviours may or may not be successful and may achieve the intended goal or another goal. It is by experimenting with chaotic behaviours that learning happens, new patterns are trained and new strategies are tested. Presence of high amount of CB could be indicative of non-expert players.

Intention and Improvisation:

Clint Hocking, Creative Director at Ubisoft Montreal, (Hocking, 2009), explored the concept of improvisation in playing games. He first quotes Dough Church defining Intention as “the ability of the player to devise his own meaningful goals through his understanding of the game dynamics and to formulate meaningful plans to achieve them using the information and resources provided by the game”. He then proceeds to define improvisation as “the highly intentional but formless and dynamic mode of play that arises when players abandon classical modes of competing with the game for control and domination, and embrace unpredictability, randomness and analog failure in a system space that supports it by not punishing them". Hocking looks at player actions in a game as a succession of moments of composition, where the player is thinking about what she wants to do, followed by execution, where the player is doing it. Linear shooters have very brief moments of composition while players spend most of the time executing actions. Puzzle games on the other hand require longer time spent composing the actions, while the execution is somewhat trivial. Lucy Suchman (Suchman, 2007) claims that "although the course of action can always be projected or reconstructed in terms of prior intentions and typical situations, the prescriptive significance of intentions for situated action is inherently vague. The coherence of situated action is tied in essential ways not to individual predispositions or conventional rules but to local interactions contingent on the actor's particular circumstances." This implies that, to a certain degree, the three classes of actions must incorporate sensitivity to the local context in terms of openness to improvisation and flexibility in the execution. Improvisation can then be identified as a fast, repeated, dynamic movement between moments of composition and execution. Intentional Behaviours are repeatedly interspersed with almost automatic Trained Behaviours and occasionally by Chaotic Behaviours. The mark of improvisation is being able to fall back on a set of TB and occasionally establish new TB by performing CBs. Intentionality doesn't arise necessarily only from having a long composition phase – planning the details of the encounter. Intentionality is involved also in the presence of a composition phase that is balanced against the execution phase. Improvised play happens as very rapid cycles between the IB, TB and CB.

A PROPOSED MODEL BASED ON THEORY OF PLANNED BEHAVIOR

This chapter describes our approach to explaining different types of intended behaviors and improvised trained patterns, based on the fundamental work on intention Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975) originally, and enriched later in 1991 by Ajzen (1991) as Theory of Planned Behaviour (TPB). In the rest of this chapter, we first briefly explain the TPB model followed by examples in games and our approach to account for intentional and non-intentional behaviors in games.

Theory of planned behavior:

In order to predict a behavior intention, Fishbein and Ajzen proposed a formula to understand the process of forming behavior intention, as follows.

$$BI = w_1A + w_2SN + w_3PBC \qquad (1)$$

Where, BI denotes behavior intention which indicates the degree of performing a particular behavior, A means attitude towards the behavior which consists of the person's belief on the consequences of the behavior multiplied by the person's degree of value on the belief, and SN denotes social norms -- how other social members would think (positively or negatively) on the behavior if the person executes the behavior. In 1991, Ajzen has modified the model by adding another factor, Perceived Behavior Control. This term means that the person's perception on the possibility of success in carrying out the behavior, denoted as PBC in this paper. Each element in the formula (1) can be weighed by an empirically determined coefficient (w_1, w_2, w_3).

Based on the equation (1), we can predict intentional actions in games. We believe that the attitude toward the behavior (A) and the perceived behavior control (PBC) can also be easily transferred into a game world. Attitude (A) in games is the game world status the player believes to be when he performs the behavior and perceived behavior control (PBC) in game means skill execution-performance.

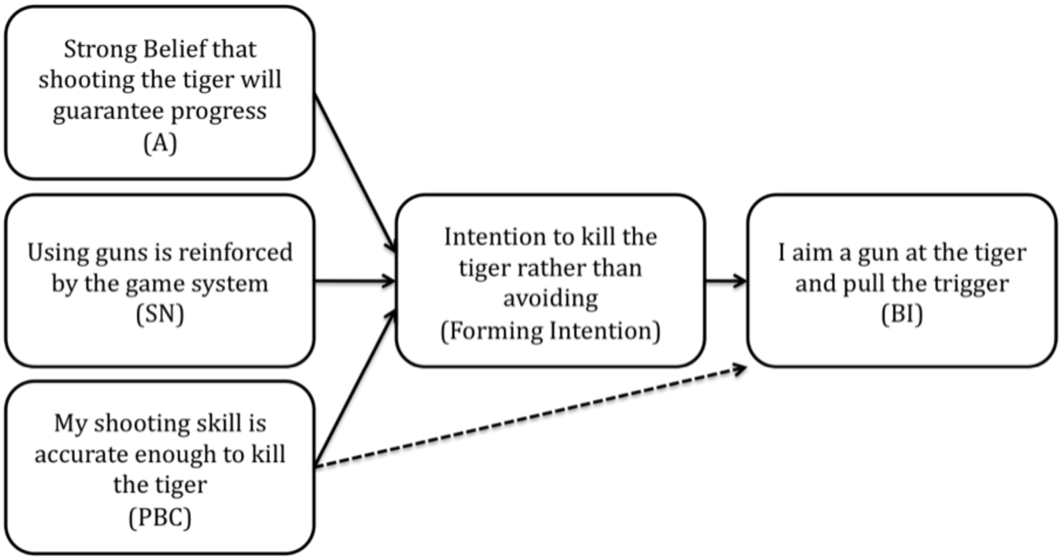

Figure 1: Theory of Planned Behaviour and example from Tomb Raider: Underworld.

On the other hand, social norms (SN) can actually mean various concepts in games. Social norms represent beliefs of what others think, what experts think, and motivation to comply with others according to Ajzen and Fishbein (1980). In games, we believe that 'other' can mean the other game players in a multi-player environment or intelligent non-player characters. Experts in games may mean expert gamers who have played the same game, or the play patterns that are expected to be performed by the game designers and the game systems.

Figure 1 provides an example rooted in the game Tomb Raider: Underworld. In the example, the player model shows the strong attitude toward the consequences of shooting the tiger in front of her (high value in A), the social norm in the game that encourages shooting (high value in SN), and has confidence in her shooting skill (high value in PBC). As a result, the player formed the intention of confronting the tiger and behavior intention to kill the tiger by shooting. While attitude and social norm, have only indirect impact on building the behavior intention through the intended goal, perceived behavior control can also have direct influence on the behavior intention, as the dashed line between PBC and BI in the figure shows.

9 categories in relation to behavior and goal achievement in game:

Once intentional behaviors are identified based on the TPB model, the rest of the behaviors can be regarded as non-intentional behavior. And again, according to our taxonomy, there are trained behaviors and chaotic behavior. Based on the behavior categories and its result in achieving the intended goal, TABLE 1 classifies 9 types of situation based on three types of behavior (IB, TB, and CB) and its consequences in achieving goals in the game. In the first three cases (1, 2 and 3) the player is fully aware of the process of forming the behavior and its consequences, while she may be partially fully aware of the consequences in cases 4, 5, and 6. Moreover, she can be even ignorant of what would happen when she executes those behaviors in cases 7, 8, and 9. In such cases, those behaviors are created randomly when the player has no alternative plans or no trained patterns to fulfill the initial goal (GI). Figure 2 illustrates the possible transitions among these 9 cases.

Table 1: 9 cases categorized based on the intentionality of the behavior and its impact on goal achievement. In the table, IB denotes intentional behavior, TB means trained behavior, and CB means chaotic behavior. GI is an initial goal, GA is a goal which could be formed during the play. Whereas GI is a goal intentionally formed by the player, GA is a goal that the player did not initially aimed at. Furthermore, GA can be a system goal that the player may even be unaware of when he performs a behavior, which may eventually result in its achievement. For example if GI is "negotiate the encounter with a tiger", then a possible GA could be "collecting a treasure chest while escaping the tiger".

	BEHAVIOR	INTENDED FOR	RESULT	NOTE
CASE 1	IB	GI	Achieved GI	
CASE 2	IB	GI	Failed to achieve any of the game goals	Incorrect belief or change in the situation
CASE 3	IB	GI	Failed to achieve GI and achieved GA instead	The player came up with a familiar behavior that he believes that it can achieve GI and luckily achieved another goal GA which he was unaware of
CASE 4	TB	learned pattern, aimed at GI	Achieved GI	The player instinctively comes up with a familiar behavior learnt during training session without knowing that it can achieve the initial goal
CASE 5	TB	learned pattern, aimed at GI	Failed to achieve any of the game goals	
CASE 6	TB	learned pattern, aimed at GI	Failed to achieve GI and achieved GA instead	The player instinctively comes up with a familiar behavior learnt during training session without knowing that it can achieve another game goal
CASE 7	CB	randomly generated	Achieved GI	Random behavior achieved the initial goal GI
CASE 8	CB	randomy generated	Failed to achieve any of the game goals	
CASE 9	CB	randomly generated	Failed to achieve GI but achieved GA instead	Random behavior failed to achieve the initial goal but achieved another game goal he was unaware of

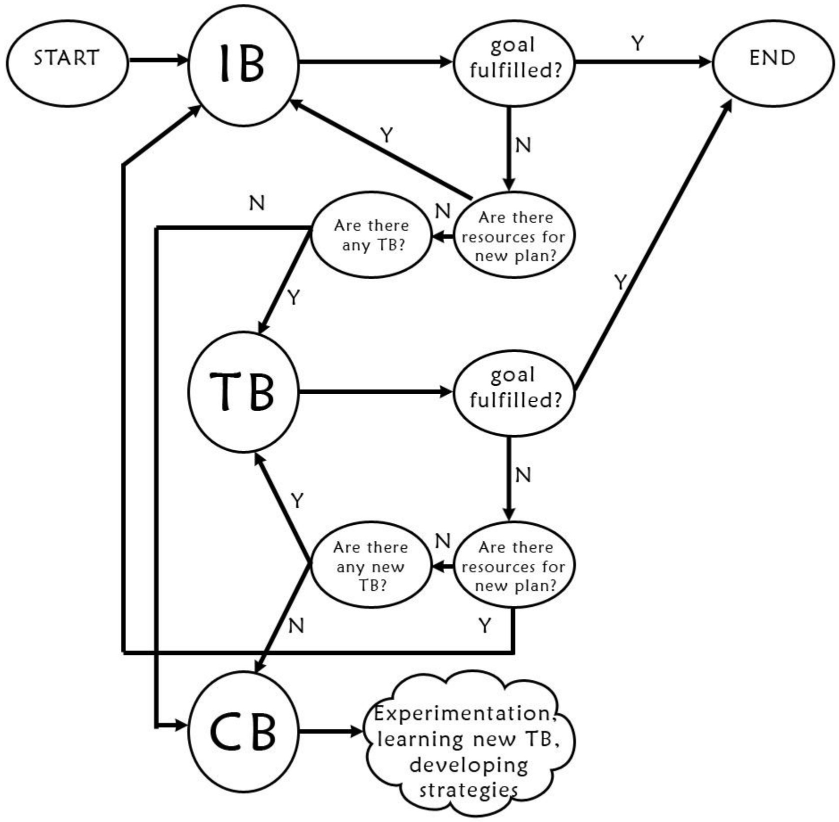

Figure 2: Transition among behavior categories. Improvisation is conceptualized as a rapid movement between IB, TB and CB.

The cases where the player is only partially aware of the consequences of the behaviors (Cases 4-9) may play an important role in expanding the player's preconception and knowledge about the game. Those cases can be also compared to the three types of patterns to construct a narrative in improvisational performance, as observed in their empirical study carried out by Baumer and Magerko (2011). Baumer and Magerko have classified three types of offer/response interaction between two actors while performing an improvisation on stage: a) Yes, And (Accept, Augment), b) Yes, But (Accept, Redirect), and c) No, But (Reject, Redirect). In the improvisation theater, the performance begins when only parts of the initial setting of the narrative are confirmed (generally from the audience), such as the main characters' profiles, the initial conflicts between the characters, and the location where the narrative is imagined to occur. Then, the narrative is gradually constructed as the actors exchange their acts. Like the player may realize that his improvised or chaotic behavior is meaningful when the game system realizes its consequences, the act offered by one improviser turns out to be relevant or irrelevant as the other performer verifies or reject the offer. For instance, one actor may perform an initiating offer friendly saying that "What are you doing, my son?", then the responder may accept the offer by saying "I'm playing with my toy, mom" or accept it but redirects it as "I'm watching video but why are you so nice to me today?" (taking the offer but redirecting the narrative in a way that the mother's character is not as supposed in the offer) or reject and redirect it as “Why are you acting like mom?” (rejecting the initiating actor’s identity as mom and redirecting the narrative flow). Although ‘Yes, And’ is ideal in most cases, ‘Yes, But’ and ‘No, But’ may develop the narrative in an unexpected direction.

Particularly, we are interested in the cases 4, 6, 7 and 9, where the player can build and revise his knowledge out of serendipity. These cases may be viewed as a first step towards building new trained patterns when carrying out those behaviors result in the success of the intended goal or another goal aimed initially but turns out to be one of the game goals. Furthermore, from a view of a third person or by the system which attempt to model the player may conclude that they are intentional behaviors even if those behaviors are not fully planned for the goal (cases 4 and 7) or failed to achieve the initially intended goal (cases 6 and 9).

IMPACT ON EXISTING PRACTICES AND FIELDS

Adaptivity is a lot more effective if based on intentional acts, skill levels and performance indicators. Predictive studies such as for example studies on player retention, also greatly benefit in terms of precision and effectiveness if a difference can be detected between highly intentional and non-intentional acts. Detecting faulty patterns in terms of misunderstandings on the functioning of the game also becomes possible. Finally, studies focusing on personality and individual differences have the possibility to become much more precise.

Our research is also related to intelligent interfaces and smart services that involve user modeling process. The research on differentiating intentional behaviors from non-intentional behaviors may have impact on intelligent interfaces on smart devices including mobile phones and light-weight smart devices such as iPad and Galaxy Tab. Especially on mobile phones, it has been getting difficult for the user to find the right app appropriate for a particular situation due to countless apps available to him. Current research on such smart interfaces can use numerous physical contexts (location, time, weather, vision, sound) as well as software contexts (messages, email, calendar items, application usage) to predict the service that is most appropriate for the situation and the user (Bellotti et al., 2008; Shankar et al., 2007). In predicting the next activity for the user, the context-aware mobile recommender system Magitti (Bellotti et al., 2008) uses probabilistic methods to build the user model from the patterns and activities of her behavior in the past. Therefore, such context-aware systems may have benefits from understanding what activities are intentional and what are not. Although there is no need to exclude non-intentional activities when building the user model, there is need to give higher weight on intentionally carried out behaviors than those behaviors non-intentionally performed which result in no utilities in achieving intended goals.

CONCLUSION AND FUTURE WORK

The framework presented here problematises the practice of building models of player behaviour based on indiscriminated gameplay metrics data. The next step along this avenue of research is the suggestion of techniques to be able to automatically differentiate between player actions as reported by metrics data. It is legitimate to actually question whether automatic detection of intentionality in players’ actions based on gameplay data is at all possible. We believe that dynamic Bayesian networks, sequence mining, expert systems and databases of possible moves and behavioural patterns can be used to distinguish intentional behavior from non-intentional behavior. We plan to continue our investigations on different types of gameplay activities in terms of intention and present a technique to automate the distinction as our future work.

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