Modeling Routinization in Games - An Information Theory Approach

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Abstract
Routinization is the result of practicing until an action stops being a goal-directed process. This paper formulates a definition of routinization in games based on prior research in the fields of activity theory and practice theory. Routinization is analyzed using the formal model of discrete-time, discrete-space Markov chains and information theory to measure the actual error between the dynamically trained models and the player interaction. Preliminary research supports the hypothesis that Markov chains can be effectively used to model routinization in games. A full study design is presented to further explore and verify this hypothesis.

Author Keywords
Information Theory; Routinization; Markov Chains; Games

ACM Classification Keywords
K.8.0 [Personal computing]: General – Games; H.1.1 [Systems and Information Theory]: Information theory; G.3 [Probability and Statistics]: Markov processes; H.5.2 [User Interfaces]: Evaluation/methodology

Introduction
Many processes in our everyday lives are performed without conscious effort like picking up the phone or shifting gears in a car. This internalization of an activity

has been described as routinization. Routinization is well researched in the context of work [21][11] and human-computer interaction [4], but has not been applied to games yet. Gameplay elements are often repetitive and thus lend themselves to routinization via practice. By formulating our own working definition of routinization in games and by using Markov chains and information theory as tools, we can make routinization measurable. This allows us to see where and how routinization happens as well as its implications.

Related Work

[22] gives an overview over AI and computational intelligence topics in games. Even though various metrics and machine learning techniques have been used to model player behaviour [20][7] [24], adapt game play on-the-fly [23], classify players [8] and to predict their behaviour [5], none so far used information theory to analyse the models. 'Game Analytics' has been a rising field in recent years [17] dealing with larger cohorts of players and not individual player interaction. In contrast, our research works with individual players and looks at routinization of gameplay.

Defining Routinization

Activity theory [10] and practice theory [15] are two fields of science where routinization has been researched. The former approaches it from a psychological perspective, while the latter developed out of social sciences.

Leont'ev [6], one of the founders of activity theory, gives the example of the routinization of manual gear-shifting while driving a car (see [10]). When learning to drive, shifting gears is a conscious process with an explicit goal. With practice, it becomes routine and "can no longer be picked out as a special goal-directed process: its goal is not picked out and discerned by the driver; and for the driver, gear shifting psychologically ceases to exist" [6]. This implies that the immediate motoric interaction is getting more and more independent of the conscious goal-oriented interaction. In practice theory, a related scientific field originating in social sciences [1][2], the routinization of bodily activities results in 'practices' that are "routinized bodily activities" which "can be understood as the regular, skillful performance of (human) bodies." [15]. In the context of our work we summarize the qualities of regularity and skillfulness as 'proficiency'.

Routinization in Games

Routinization in activity theory and practice theory has been applied to work [21][11] and general human-computer interaction [4], but not specifically to games. In games, routinization means that the interaction with specific game elements is the less consciously executed, the more practiced the player gets. Different levels of interactivity are routinized differently: From the high-level process of solving a puzzle to the basic action of performing a dash. For example, in Portal 2 [19], a 3D puzzle platformer game, one would expect the running and gunning to become more and more routine whereas the goal-oriented task of solving the puzzles stays as conscious as it is in the beginning.

Routinization is individual to each combination of player and game (element). Even though most players play a given section of a game quite similarly, individual players have slightly different and unique interaction patterns, just like different drivers exhibit different interaction patterns when driving the same car.

Repeating tasks in games is intuitively a requisite for routinization, as analysed by Ohly et al. [12] and intuitively requires a stable environment. A stable environment (defined along the lines of Ouellette and

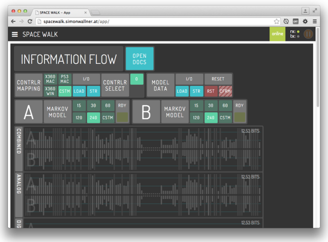

Figure 1: A screenshot of the web based analysis tool "Space Walk."

Wood [14]) is provided if the goals of the activity are not influenced by it. In games, the environment includes the actual physical environment that the human player is in as well as the virtual world of the game.

For the purpose of our research, we define routinized play as individual[15], repeatable [12] and self-similar[14] and as appearing proficient[15].

Modeling Routinization

Based on this working definition, we formulate a model for routinized play and measure how well our observations fit that model. For practical and economical reasons, the model should be as generic as possible but it also has to be adaptable to individual players and games. The model should be suitable for ad hoc analysis during the experiment as well as post hoc analysis after the experiment has concluded. Ad hoc analysis allows us to use the model in exploratory and real-time settings, for example during a playtest[16] where data is only available up to the current time.

We chose discrete-time, discrete-space Markov chains as the model class for our approach. Markov chains are very general and only require a small set of a priori assumptions. They are not black boxes, and can easily be understood and visualized to gain further insights. They can be trained on-the-fly and since routinized actions are expected to be self similar, the parameters (i.e. the edge weights) are expected to converge to a stable configuration in the face of routinized play. This leads to our working hypothesis: **Discrete-time, discrete-space Markov chains can be used as a general model for routinization of specific gameplay elements.**

Measuring Model Error

A tool called Space Walk[1] was created as the technical basis for our research (see Figure 1). Space Walk is a real-time telemetry and analysis application. It runs in a standard web browser and can be easily extended via plugins. For the purpose of this study, a plugin was created that trains Markov models in real-time and on-the-fly and visualizes both the resulting model fit, and the models themselves.

We use information theory to assess how well the observed data fits our models by measuring the resulting information content of the user's input. Information content (also called 'Self-Information' or 'surprisal') describes how much information is gained from having observed an event. The information content I of an event x is solely dependent on its a posteriori probability $p(x)$ and can be calculated with the following formula:

$$I(x) = \log_2 \left(\frac{1}{p(x)} \right) bits \tag{1}$$

The more predictable an event is, the less information it carries and vice versa. As an example, consider learning that a friend is awaiting a baby. Depending on the person, this might be surprising on its own, but now consider learning that this person is actually awaiting twins or even triplets. The probability of that event is lower and thus the information gained by learning about it is higher.

Information content offers a practical way to measure the model error in bits. If the model predicted user input well, the a posteriori probability $p(x)$ is high, and thus the information content $I(x)$ is low. In the limiting case

[1] `http://spacewalk.simonwallner.at/`, MIT license

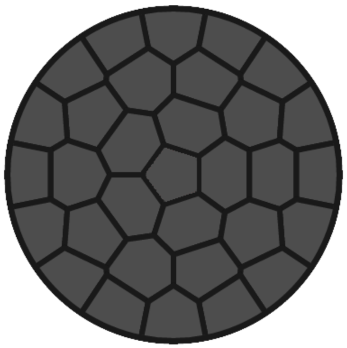

Figure 2: The XY-space of an analog stick discretized into approximately evenly sized cells.

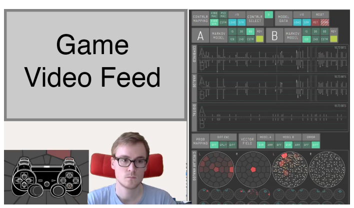

Figure 3: The setup of the pre-study. The individual video feeds have been combined with the OBS software.

where the model matches exactly and the input can be perfectly predicted, the information content reaches 0 $(I(p(x) = 1) = ld(1/1) = 0)$

Space Walk samples at 100ms time intervals to discretize the user input in the time domain. The interaction space of analog controls is discretized into approximately evenly sized cells (see Figure 2).

We are aware that input from analog sticks, analog triggers and buttons (the 'input groups') is generally not stochastically independent. However, we use stochastic independence as a justifiable modeling assumption. The additivity of information content allows us to model these input groups individually and subsequently add up the partial model errors.

The models only represent data from the last 15 to 240 seconds. 'Shorter' models can adopt quicker but also suffer more undersampling problems that lead to unwanted spikes in the data. To mitigate this problem, instead of using the scalar maximum likelihood estimator for probability values $p(x)$, we use the probability distribution of this statistic $(p(x) \sim Beta(\alpha, \beta))$.

Preliminary Results

Our hypothesis is based on results of an exploratory pilot study with various games from different genres. A combined video recording of the game, a video feed from the player, a direct visualization of the game controller and the computed model error has been recorded during the test session (see Figure 3). A post hoc analysis of the data showed different patterns emerging from different games and gameplay elements. By using the above described models and our definition of routinized play we observed the routinization within the individual levels in Super Meat Boy [9], a 2D action platformer game. The model dynamically adapted to the routinization of the player, which resulted in a good overall model fit, thus we strongly believe that Markov chains are an adequate formal model for routinization.

Proposed Method and Procedure

For the experiment, we will use discrete-time, discrete-space Markov models as described above. The sampling frequency in the time domain and the discretization in the spatial domain will remain the same as used during the pilot study and will stay constant throughout this experiment. In this study we will focus on individual users, and will cross reference their individual results to find common trends and to identify outliers.

Test subjects will be asked to play a number of levels from Super Meat Boy in one play session. Super Meat Boy serves as a good test bed, because the gameplay is rather uniform. Beating a level usually only takes a few seconds but requires several attempts. During this process, all inputs via the game controller, a video feed of the game as well as of the tester will be recorded for post hoc analysis.

In a first step, the collected data will get categorized on a qualitative scale from 'not routinized' to 'highly routinized', according to our definition of routinized play. In a second step the models will be created using the data and the model fit is computed. The models are dynamically trained and of finite length in the sense that at any time, a model only represents the data from the last n seconds. The effects of different model lengths will be evaluated.

The results of the individual testers will then be grouped by category to analyze the distribution within each category and to see where outliers are located. Outliers are important, because they hint on the limits of the model and thus help to refine it in future iterations. Further statistical analysis will be used to analyze to what degree model fit can be used as a predictor for the attributed categories.

Outlook & Implications

After this initial study we are planning further studies to analyze the effect of the model design parameters that have been assumed as fixed in this study. These are the sampling frequency of the user input and the discretization used on analog inputs.

Further, Markov chains can be used as a very basic model for interaction in general. In this context we interpret information content as the amount of interaction or as the information encoded in the interaction. This more general interpretation can be used to analyze structural complexity of input schemes, e.g. as a generalization of [18]. The same process could be used to detect unexpected gameplay patterns in user tests of commercial games. This could even lead to commercial use cases of the described system.

Another interesting area is the case where interaction becomes completely deterministic, e.g. if a player hits every note in a perfect Guitar Hero[3] game. When interaction becomes completely predictable, the information content of the user interactions approaches 0. Can this extreme case still be considered interactive, and if so, where does the interaction take place, if we assume that no information is flowing from the player to the game? Thinking this further, how often does the player feel in control when she is actually not having any significant influence on the system? This phenomenon, called 'illusion of control', has been exhaustively researched (see e.g. [13]) but being able to measure the information content of interactivity could contribute to the field. In networked games, predicting player movement is a basic technique for mitigating latency issues [5]. A stochastic player model can help to fine tune movement prediction. In games where the player controls a whole team, like soccer simulations, the A.I. could use stochastic models to better tune the behavior of team mates to the players habits.

Modeling player interaction and applying information theory opens up much more research questions than we have space to discuss here. With our work we hope to have taken the first step into this new field and we are looking forward to future results.

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