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Comparison of similarity measures to differentiate players' actions and decision-making profiles in serious games analytics

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A B S T R A C T

Three Gameplay Action-Decision (GAD) profiles: *Explorer*, *Fulfiller*, and *Quitter*, have been identified based on individual's decision-making actions and navigational behaviors *in situ* serious games. The ability to profile trainees using serious games can yield new analytics and insights towards training and learning performance improvement, including the identification of weaknesses or potential training needs in the players towards adaptive training, and the creation of new diagnostics for prescriptive training, retraining, and remediation. Similarity measures of players' in-game *course of actions* (COAs) have been shown to be a viable approach in differentiating novices from experts in serious games.

In this study, we examined and compared several popular similarity measures to see if any measure, or combination of measures, would be viable in differentiating players based on their GAD profiles in serious games. Our findings revealed that similarity measures, while significant in their predicting abilities individually, could gain more strength from one another in combination. More research is needed to create or develop new metrics and methods for players' action and behavioral profiling in Serious Games Analytics.

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1. Introduction

A *similarity measure* is a statistical function to quantify the (dis) similarity of two objects. Although originally created for analyses in phytology (Jaccard, 1912) and record linkage (Winkler, 1999), the measure of (dis)similarity between two objects has become indispensable for research in data mining, information retrieval, and machine learning. Depending on the study, these two objects being compared can be text strings (record linkage), documents and audio files (information/audio retrieval), photographic images and videos (computer vision), DNA sequences (genetics), vectors (computer science), and many others.

Mathematically, (dis)similarity metrics are bound by the value from 0 to 1. When the two objects are completely different (i.e., dissimilar), the value is 0; when they are identical (i.e., similar), the value is 1. Dissimilarity of the two objects is also identical to the (edit) *distance* between the objects. The relationship between *similarity* and *distance* is:

$$\text{Similarity (A, B)} = 1 - \text{Distance (A, B)}$$

Similarity measures have been applied in high-stake areas such as facial recognition (El-Sayed & Hamed, 2015; Vezzetti & Marcolin, 2015), fingerprint analysis (Ghany, Hassanien, & Schaefer, 2014), cheminformatics (Bajusz, Rácz, & Héberger, 2015), DNA analysis (Kobayashi & Satoshi, 1993), biometrics (Mansukhani & Govindaraju, 2005), as well as fraud (Rüping, Punko, Günter, & Grosskreutz, 2008) and plagiarism detection (Stein & zu Eissen, 2006). Even social entertainment applications such as name-that-song, auto face-tagging in Facebook, online matchmaking, and the Google Search Engine all make use of similarity measures in one way or another. Since many of these applications can also be monetized for profit (Seif El-Nasr, Drachen, & Canossa, 2013), understanding the power of these measures becomes a topic of interest.

1.1. Performance assessment in serious games

According to a recent report (BankersLab, 2013), about 25% of Global Fortune 500 companies have already adopted serious games for simulation and virtual environment based training. These

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trainings are particularly useful for acquiring skills and cognitive processes not easily taught in a classroom setting, such as strategic and analytical thinking, planning and execution, problem solving, decision-making, and adaptation to rapid change (Foundation of American Scientists, 2006). More recent accounts also added rehabilitation (Cornforth et al., 2015), patient choice education (Mihail, Jacobs, Goldsmith, & Lohr, 2015), and expertise training (Loh & Sheng, 2015a).

As players interact with the gaming/training elements in the serious games, they generate action data that can be traced using software telemetry (Chung, 2015; Zoeller, 2013) and other specifically created assessment frameworks, such as *Information Trails* (Loh, 2012, pp. 123–144; Loh, Anantachai, Byun, & Lenox, 2007). A database of captured action data can be (data)mined to yield analytics and insights for training and improvement: e.g., visualize players' navigational paths (Chittaro, Ranon, & Ieronutti, 2006; Loh, Sheng, & Li, 2015; Zacharias, 2006), measure changes in their proficiency levels (Loh & Sheng, 2015a), differentiate the novices from the experts (Loh & Sheng, 2014, 2015b), and diagnose potential problems (Liu, Shen, Mei, Ji, & Miao, 2013; Mihail et al., 2015), to name a few. Hopefully, in the near future, serious games can mature into the "tools for improving decision-making skills and performance" (Krulak, 1997; Michael & Chen, 2005; Sawyer & Rejeski, 2002) – as originally intended.

1.2. Gameplay actions and behaviors

Players' actions and behaviors *in situ* serious games can be particularly powerful as evidence in understanding how people solve problems (i.e., decision-making strategy) when faced with obstacles inside the gaming habitat. As a research tool, serious games create an opportunity for researchers to observe and infer how people make decision while problem-solving.

Many entertainment and serious games make excellent use of puzzles and obstacles in game to elicit player engagement, requiring them to pit their wits against the designers' 'obstacle course' to progress the storyline. For example, games like *Biohazard*, *Castlevania*, and *Plant vs. Zombies* require players to avoid incoming enemies but effect attacks to move forward. Variations on this theme are games like *Call of Duty* and *Assassin's Creed* that include 'missions' to better engage players. These missions can range from reconnaissance, to securing assets, to search and rescue. Newer *Tomb Raider* and *Uncharted* series even implement rock climbing, rappelling, and treasure hunting as missions to give sedentary gamers a taste of outdoor adventures and extreme sports. No matter what the guise is, missions are *problems* created by designers for players to overcome.

Essentially, (serious) games are made up of a series of missions or problems waiting to be solved. From an instructional designer's point of view, these problems are very similar to the learning and training goals of a learning organization, such as the military or business corporations. A problem that is too difficult may cause the players to give up without trying. If the 'problems' are properly executed, players become enticed or willing to try different options – e.g., repeating an action until the skill has been perfected, trying different approaches until a workable solution is found, and searching for alternative routes to avoid a 'defeating' outcome. The first two options require *deliberate practice* (Ericsson, Prietula, & Cokely, 2007) for performance improvement, while the last one calls for wits.

Gameplay analytics from players' (problem-solving) actions and behaviors have been successfully used in usability and user experience research (e.g., Tychsen & Canossa, 2008; Zacharias, 2006) to improve gameplay through better balancing (Desurvire & Seif El-Nasr, 2013; Pruett, 2010), visualizing players' navigation paths (Chittaro et al., 2006; Thawonmas, Yoshida, Lou, & Chen, 2011), predicting player moves (Gambs, Killijian, & del Prado Cortez, 2012; Weber & Mateas, 2009), profiling players by gameplay activities (Moura, Seif El-Nasr, & Shaw, 2011; van Lankveld, Spronck, van den Herik, & Arntz, 2011), dynamically adapting the gameplay (i.e., adaptive gameplay) to increase player entertainment (Charles et al., 2005; Gow, Baumgarten, Cairns, Colton, & Miller, 2012), and many others. This body of research can help serious games researchers to find means to put activities profiling into realizing training performance improvement: e.g., how to better design serious games for training and for adaptive learning. Players' actions and behavioral data in serious games can be especially powerful for the training research because these data are direct evidence of players' decision-making strategies when solving problems, or during serious gameplay.

1.3. Serious games analytics

Compared to the many years of game analytics studies (Medler & Magerko, 2011; Seif El-Nasr et al., 2013), serious games analytics is still in its infancy. Fortunately, some researchers from around the world have taken an interest in the topic (Loh, Sheng, & Ifenthaler, 2015a). A caveat is that while the data analysis strategies of action data from (video) games vs. serious games may be similar, the foci on performance improvement are completely different. Many user profiling projects involving commercial video games seek to enhance the 'enjoyment' value of players, while those with serious games need to *additionally* include how to increase players' skill acquisitions and levels of expertise (Loh & Sheng, 2015a; Loh et al., 2015b).

Dreyfus (2004; Dreyfus & Dreyfus, 1980) described five stages of expertise in skill acquisition, namely *novice*, *competent*, *proficient*, *expert*, and *master*. Because corporate training is more short-term (from a few days to a few months) than long-term (spanning a few years), only the first three stages of expertise are achievable through corporate training, in practice. The last two stages are only attainable via a longer period of deliberate practice – after spending a few years working in the organizations. During (serious games based) training, users' proficiencies are expected to improve from the lower level of novice to either competent or proficient.

The traces of players' in-game Course of Actions (COAs) can be converted into an alpha-numerical string or sequence to facilitate similarity-measure analysis (Fig. 1). One should take care to ensure that the COAs traced contain meaningful information that is useful in explaining player profiles. Excessive tracking of gameplay data can result in GIGO (Garbage In, Garbage Out) that impedes the serious games analytics' process.

Loh and colleagues (Loh & Li, 2015; Loh, Sheng, & Li, 2015; Loh & Sheng, 2013, 2014) demonstrated that the abovementioned COAs can be quantified as serious games (learning) performance by comparing the COAs of novices against that of the experts' using pairwise similarity-measure analysis. Players who behaved more like experts would receive higher similarity scores, while those at a further distance from the targeted expert-level would receive lower scores. As the majority of similarity metrics/coefficients are mathematically bound from 0 to 1, the similarity scores can be easily interpreted by laypersons as a type of performance ranging from 0% to 100%.

1.4. Players' Gameplay Action-Decision (GAD) profiles

Game player profiling is not new. A quick search using Google Scholar with the keywords, *video games* "*player profiling*," returned 257 documents, while adding "*player modeling*" to the mix raised the find to 828. The earliest Google record showed two patents on