Game Analytics and Game User Research

Magy Seif El-Nasr  
Colleges of Arts, Media, and Design & Computer and Information Sciences, Northeastern University  
magy@neu.edu

Heather Desurvire  
User Behavioristics Research, Inc., Interactive Media Department, University of Southern California  
Heather3d@gmail.com

Bardia Aghabeigi  
College of Computer and Information Sciences, Northeastern University  
b.aghabeigi@gmail.com

Anders Drachen  
College of Arts, Media, and Design, Northeastern University and Game Analytics  
andersdrachen@gmail.com

Abstract

Game User Research is an emerging field that investigates the interaction between players and games and the surrounding context of play. Game User Researchers have explored different methodologies from e.g. human computer interaction, psychology, interaction design, media studies and the social sciences, extending and modifying existing methodologies to the environments that compose digital games with their many varieties, including, but not exclusive to, social games, casual games, and serious games. In this article, we will specifically focus on quantitative analytics of in-game behavioral user data and its emergent use within the Game User Research community. We will discuss a case study outlining its use and benefits with examples of current collaborations between the authors and game companies. In addition, we will outline open problems that emerged from the Workshops on Games User Research held at Computer Human Interaction and Foundations of Digital Games Conferences in 2012.

1. Introduction

Games User Research (GUR) is a new emerging field that focuses on developing an understanding of the users (or players) and how they interact with interactive playable experiences. This is an important area of investment for the game (and interactive entertainment) industry as it is essential for game companies to produce games that engage players. A substantial degree of adaptation has been necessary adopting user testing methods from outside the games industry, as games are software applications focused on user experience, and because games are often designed not to be as effective and efficient as possible – but rather challenging. This makes games somewhat different beasts as compared to productivity applications. The GUR community has thus focused on using, extending and adapting methods within the field of HCI (Human Computer Interaction) to address the measurement of player experience, engagement and user behavior. Many methods have been discussed and proposed for this purpose. This has been the subject of few books, notably Katherine Isbister’s edited book on Game Usability (Isbister and Shaffer, 2008). In addition, to the standard methodology from HCI, social sciences and psychology, Seif El-Nasr et al. (Seif El-Nasr et al., 2013) have devoted a book to focus on a game analytics, an area that overlaps with Game User Research, and which has proven very lucrative and rich gaining powerful momentum in industry and research, notably for persistent, social online games such as World of Warcraft, FarmVille, and Bubble Island.
In 2011 and 2012 the authors in collaboration with other predominant figures within the area of Games User Research, such as Katherine Isbister, Regina Bernhaupt, Lennart Nacke, and Alessandro Canossa, held three workshops on the area of Games User Research stimulating discussions between the industry and academia to target the development of the field, discuss methodologies and outline open problems within the field. In this article we will provide an introduction to game analytics in GUR, its value and current use, and future directions.

2. Current use of Analytics within Game User Research

There is currently a cache of methods used in industry and academia for identifying and understanding the player experience (PX). Methods span both qualitative and quantitative analysis methods. The intent is to assist designers in improving the game design, and thereby the game experience, to both meet their intent and most importantly, to increase the pleasurable experience of the players and thereby learning/training outcome, revenue, or similar.

The most utilized GUR methods used in the game industry are: think aloud, RITE testing, heuristic evaluation, interviews, playtesting, and A/B testing. Game analytics in particular is emerging as a new lucrative area of study and method for supplementing and augmenting the already existing GUR methods. Figure 1 shows an increase in use of game analytics as a search term on Google during 2006-2012, indicating the increasing communal interest.

Fig. 1. Google Trends analysis of the use of game analytics, -telemetry and –metrics and game data mining via Google search terms. The tree terms “game analytics”, “game telemetry” and “game metrics” are to some degree interchangeable, but “game analytics” is by consensus emerging as the term applied to analytics practices in games in the game industry. In comparison, the search term “game user research” barely registers in Google Trends. Game data mining, another term used in the industry for the specific application of data mining methods on analytics data, starts emerging around 2009.

Game Analytics has become a popular expansion to existing GUR methods because of its ability to deliver quantifiable numbers, which are easily interpretable, reduce high-dimensionality behavioral data to patterns, and not the least the explanatory value of visualizing player behavior graphically, which when for example overlaid over game environments (e.g. Figure 3 below) provide direct insights to designers about how players utilize the game assets. Analytics has had such a big impact that it is becoming common to see online games ship unfinished, and continuously be refined and redeveloped through the use of user behavior data collected online (formally referred to as telemetry data). These are used to find bugs and problems in the software, and to further develop and tune the games design and system mechanics through its lifetime (Seif El-Nasr, Drachen, & Canossa, 2013). Behavioral telemetry data has also been used by game user researchers for all types of games during production as a method of gauging what players are doing and supplementing that information with other playtesting methods (Seif El-Nasr, Drachen, et al., 2013). Fundamentally, telemetry data provide a high-precision, quantitative measure of behavior that no other GUR method can easily provide. A good example of the method merger was developed by one of the earliest adopters of analytics in GUR, Microsoft Studios Research.
Microsoft developed a visual analytics system called TRUE, which uses spatial visualizations of player activity correlated with other qualitative data from RITE testing (Kim et al., 2008). This kind of approach is effective to pin-point issues with engagement and difficulty and combine the ‘what’ gained from behavioral telemetry with the ‘why’ gained through qualitative feedback.

A common approach to analyze player behavior telemetry is to convert the data into a more meaningful set of aggregated metrics, called Game Metrics (Mellon, 2009; Mellon & Kazemi, 2008). For example, login and logoff times of a user provide a set of raw telemetry data which can be converted to a “playtime” metrics, which represents the total amount of time a user spent interacting with the game. Game metrics can then be visualized using a variety of methods depending on the data and the goal of the analysis. A common visualization is the heatmap: Heatmaps are fundamentally density maps of specific variables in 2D or 3D space, and thus they are useful for displaying the kind of spatio-temporal data extracted from avatar movements. Heatmaps are heavily used for their utility in spotting problem areas within level design, notably in multi-player and massively multi-player games (Seif El-Nasr et al., 2013). Other methods, such as network and graph visualizations, are used for demonstrating social metrics, and in the social domain, one of the most interesting current topics is the problem of graph layout.

In addition to the use of heatmaps or simple graphical visualization, there has been work on developing more dynamic and interactive visual analytics systems to suit the questions asked by game user researchers. These visual analytics systems often combine standard visualization methods as a tool set for game user researchers (and other stakeholders, e.g. designers) allowing them to play around with data and investigate hypotheses and answer questions. For example, Zoeller developed a visualization system for the major commercial game Dragon Age. He used several standard temporal techniques, such as plot based diagrams, index charts, and stacked graphs to visualize game metric data. Medler used similar temporal visualization techniques in the Data Cracker system for the game Dead Space. Drachen and Canossa utilized a Geographical Information System to analyze player behavior in games such as Kane & Lynch and Tomb Raider: Underworld. Seif El-Nasr et al. have demonstrated the use of visual analytics systems (Pathways and Dados) for RTS and RPG game genres, including Dragon Age. These methods are all discussed in (Seif El-Nasr et al., 2013).

In addition to visualization techniques, to show patterns of user behaviors and especially temporal patterns, data mining algorithms are often used. Game data mining has become central to online business models, and has become a key approach towards finding patterns in player behavior for informing design as well as for making business decisions.

3. Challenges and Open Problems

One conclusion from the workshop at CHI 2012 was that the use of analytics is important as it supplements the results that can be achieved by other GUR methods, such as heuristics, playtesting, and think aloud. However, it can be a challenge to mix the approaches as analytics and user research originate from two different areas of software development. Furthermore, understanding what behaviors to collect, how to visualize it in a useful way for designers, and how to present information quickly enough to enable decisions to be made, remain open questions.

As discussed above, games user researchers have at their disposal several methods that they can use to assess and evaluate their games. Each one of these methods has pros and cons associated with it. Telemetry and analytics, for example, is a great resource that can tell researchers what players are doing, but it cannot directly identify the reasons for players’ actions. Thus, mixing different techniques is important, as outlined by many authors in the book by (Seif El-Nasr et al., 2013). Therefore, one of the open problems facing GUR is how to develop mixed-methods
approaches that will leverage the advantages of the different methods to allow the team to assess the game in a rapid, financially viable manner, which provides actionable insights.

Another challenge is concerned with the development of techniques allowing game user researchers to make sense and be able to construct a coherent and clear narrative about players’ behaviors and emotions using the collected data. This is an interesting challenge that opens the door to new opportunities in areas such as: visual analytics, tools for displaying and querying quantitative data, etc. The idea of developing tools that will allow designers and other stakeholders to query and visualize data from players is gaining momentum, lately. This was one of the major models that Zynga pushed forward (Seif El-Nasr et al., 2013) and led to the success of their analytics system and business strategy/model, since copied by an entire new segment of the game industry. However, standardized methods and tools for such a system have yet to be published, although any of the plethora of game analytics-focused middleware providers have emerged in the past 2-3 years may eventually provide the answer.

To address some of these challenges, we present a case study, where designers and a research team explored the use of visualization and metrics to understand what types of metrics and visualizations were of value to the development team.

4. Case study: Northeastern University and Blackbird Interactive

At the Game User Experience and Design Research Lab at Northeastern University and School of Interactive Arts and Technology at Simon Fraser University we have been working in collaboration with the game industry to specifically develop new mixed-methods to abstract and visualize telemetry data and correlate them with other sources of data to evaluate and understand how to develop more effective game user research tools and methods that can aid designers in their development process.

In 2011, we started a close collaboration with Blackbird Interactive in Vancouver. The company is in the process of releasing a social RTS (Real-Time Strategy) game on Facebook called Hardware. Our collaboration focused on developing a game analytics system, which is composed of telemetry collection, pattern abstraction and the development of a visual analytics system to assist with game user research, notably towards enabling designers in understanding what players like or dislike, what they have problems with, etc.

The first phase of this collaboration concentrated on developing a set of metrics, i.e. aggregate measures of user (player) behavior, that were relevant to the company and designers. We had several weekly meetings with game designers, where we collected a series of questions about what they would like to measure in order to evaluate the effectiveness and appeal of the games’ design. Behaviors of interest included players’ progression in the game, and how players collect and consume economy resources. We then started to define a set of concrete metrics to answer related questions and to break down each metric into telemetry data to be collected. Once we developed a set of metrics, we then programmed the telemetry system to collect the needed metrics.

To allow designers to make sense of the data, it was obvious that we would need to use visualization techniques and develop pattern or data abstraction methods to allow us to scale visualizations from hundreds or thousands of data points across up to dozens of variables, to something more manageable for designers to grasp – i.e. to reduce the dimensionality of the dataset and focus on any important patterns in player behavior. However, the question was what techniques are needed and of value, given the game and the designers’ questions and needs. In order to answer these questions, we developed a comparative study comparing different visualization and reporting techniques. In developing and comparing visualization strategies, our goal was to develop a system that will help designers understand players’ behaviors over time and can follow their trajectories.
In the following sections, we will discuss the system developed as well as the visualization techniques. We compared the visualization techniques through interviews with game designers at Blackbird. In these interviews, we asked them to specifically sketch improvements to the system to enhance the visual rhetoric of the system. Below we discuss the results.

4.1. The System

The system we developed is composed of several tools to track and visualize player behavior. These include: Temporal graphical reporting tools, such as: Index Charts, Stacked Graphs, Horizon Graphs, and Spatial visualization tools using: Spatial Bubble Charts, Flow Maps, Choropleth Maps, Graduated Symbol Maps, Cartograms, static and dynamic Heatmaps.

All methods we experimented with and implemented used the existing reporting engine called JasperSoft. Since the point is to evaluate the contribution of the visualization with the design team, the specific software contribution will not be discussed in detail here, but rather the best visualizations that can serve the design team is of value.

We integrated several tools and methods into one rich client program and a web server version (for generating reports for designers, producers, and marketing team). The system is composed of the following subsystems:

- **Data Storage Subsystem:** game telemetry is logged into text files (compressed JSON) using the game client. We store the text files in Amazon S3 cloud servers, then process those text files into Infobright database using an in-house ETL system. This data includes time stamps for when players started and ended a session, the units which they have purchased, the check points they have visited, the camera interactions, combat events, social interaction events, etc. As the game is in beta mode, the number of users is limited, but as it grows to captivate more users, then map/reduce techniques, such as Amazon EMR, Hadoop, Hive, need to be applied so that data can be prepared for metric calculation easily and efficiently. We expect to have more than 50,000 users by the end of project.

- **Data abstraction and Metric Calculation:** we use simple aggregation methods to represent the data in a form that can be used for visualization purposes. The aggregation methods we use include sum and counting, averages, variance, and groupings based on temporal windows and spatial constraints. Even though these computational methods are basic, they serve as strong indicators of players’ interactions over time and space, which need to be defined accurately to answer designers’ concerns about specific user interactions. For example, grid based matrices can be a good representation of how often players have navigated different areas, by associating each area of a map with a grid cell and counting the number of times players navigated through those places. We then create a good data model, which is used for visualization techniques, such as Heatmaps, to answer designers’ questions about how players interact with different game locations.

- **Visualizing and reporting abstract data:** We use Jasper’s reporting engine to experiment with different ways of visualizing data. The selected system is connected with an Infobright data middleware, which includes aggregated data from the first step and computed data structures from the second step.

4.2. Visualizing Player Progress over time and space

The game design team at Blackbird wanted to visualize player progression over time and space, specifically how fast beta testers progress over the game, reach new levels, and discover new spatial game-play fields. To answer these questions, we defined some basic metrics, which track a specific user XP (experience points) over time, and its corresponding playing level. We also collected other telemetry data, such as player assets (vehicle units in this game), and their available bank money at different points of game-play especially in moments that their experience points (progress element) changed. Then we made a comparative report module, which uses simple time
series diagrams (Index Charts method and small multiples technique) to depict these changes for a specific user (see Figure 2 as an example).

![Diagram](image)

**Fig. 2.** Comparative diagrams for user progress over time.

The figure outlines four different metrics; each represented as an index chart, using a small-multiples visualization technique. The top left diagram shows the player experience points over time, and the one on the right represents the level number which is closely related with previous metric, the bottom left chart outlines the player’s bank changes over time, and finally the bottom right one shows units capacity (Army size) over time, this visualization can be applied to a group of users, or an specific player in the beta test group. As observed by game analysts, the number of army units has a high positive correlation with player experience points, and level number, while the drops in bank values represents spending money on unit facilities and increase in army size. Thus, this set of diagrams shows an important relationship displaying how resource consumption (bank money), and resource gain (increase in army size number) can impact player’s progress.

We also developed an animated flow map, which can show how a beta player progresses over space and time. This visualization includes the following features:

1. A Time-Line which represents the minutes of game-play and can be altered by the designer to any moment from beginning of play
2. A resolution box, which represents the scale of time in flow map
3. A spatial and zoom-able map, which can be altered using mouse drag (to pan) and mouse wheel (to zoom in/out)
4. An animated button, which simulated the flow map from the beginning and can be stopped at any location

Figure 3 (a-c) shows an example. As you can see from the timeline that designers or analysts can see the flow of a specific user from one time to the other. The green arrows in the screenshots (figure 3) show the direction of player’s army movement from one game zone to the next one; the red areas show the sections that have been discovered, but the resources has not been consumed at that specific point of time. The third image shows a zoomed version for a specific area of the map, to better investigate how resources has been discovered, missed, or consumed.

The figures show activity at time 90 then 239. As shown, the user started exploring initial areas of the game map, and then followed a unique path toward the ending sections in a counter-clockwise manner. This is contradicted to the designer’s intention. The designer wanted players to follow a clockwise path toward the ending regions, and thus made the reverse scenario very difficult. This was interesting for the designer to see.
Designers also wanted to understand player’s behaviors in terms of the economic variables within the game. This was important to visualize, and flow maps as shown in figure 3 above were important for gauging these variables. As you can see from the figure, we used the red color circles to represent areas where resources were discovered but not consumed, and grey colored circles show the zones where resources have been consumed. This visualization allowed designers to better understand players’ navigation over time and space dimensions. It also allowed them to focus on specific players with different experience levels, and captivate their progress. After showing these visualizations to game designers they had a better understanding of how beta players explored different fields spatially during the beginning first couple of days of their game-play. It also helped them to relocate some areas, which they expected to be reached earlier, but never accessed because of geological remoteness, and provided some insights about spatial exploration of game zones over time, and whether it matches with the intended narrative and direction.

5. Concluding Remarks

The case study above showed an example of how player behavior analytics can be performed and what designers feel are important ways of visualizing the data. However, the process employed was time consuming and does not scale well to larger productions or across game productions. We outline two main findings based on the workshops and our own work: (a) visual analytics software is important to enable designers to experiment with the data and resulting visualizations towards obtaining actionable insights, (b) a way of abstracting data and showing patterns and anomalies in behavioral data is important to enable and assist designers in their work process. Pattern finding requires data mining techniques underlying the visualization techniques, which are flexible towards enabling querying and restructuring of results from the designers.

One lesson echoed within the GUR workshops is that data from telemetry alone is not sufficient for game user research, and need to be supplemented and mixed with other data, specifically qualitative data to enable more in-depth understanding of the context within which the players are playing. Thus, as outlined above, an open problem is how to develop mixed methods approaches correlating telemetry with other types of data across multiple data sets, especially when the game is constantly being revised. We believe there is a great opportunity to further develop mixed-methods techniques that can enrich understanding of player behavior to enhance game design.

6. References