

# 1

## Profiling in Games: Understanding Behavior from Telemetry

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### Abstract

The availability of large scale game behavioral data has led to a tremendous amount of attention to business intelligence in game development and -research. The analysis of player behavior has rapidly emerged to become an integrated component of game development, and is used to address a range of challenges such as improving game design, manage monetization, predict behavior, recommend games, detect fraud or to build an understanding of human behavior in online environments in general. One of the key challenges in contemporary game analytics is pattern finding in behavioral telemetry, and the construction of actionable models of behavior based on patterns. When applied to players, this process can be broadly referred to as profiling. There are a number of challenges in behavioral profiling, including the constant growth in data volume, the variety (dimensionality) and volatility of big data in game development. In this chapter the current work in behavioral profiling in digital games is described and analyzed, and the state-of-the-art established. The techniques used for behavioral profiling in games are described across descriptive statistics and machine learning. Furthermore, a number of examples are provided that covers a range of techniques from machine learning: clustering, archetypal analysis, decomposition into directional components and decision trees. Each have specific advantages in overcoming the challenge of extracting interpretable behavioral profiles from behavioral game telemetry data.

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## 1.1 Introduction

The game industry is facing a surge of data, which results from increasingly available highly detailed information about the behavior of software and software users. The data can come from a variety of channels, e.g. behavioral telemetry, user testing, surveys, attribution models, forums etc., be high-dimensional, time-dependent and potentially very large Drachen et al. (2013b); Sifa et al. (2014a); Feng et al. (2007); Hadji et al. (2014). The old adage of big data having volume, velocity, variety and volatility holds very true for behavioral telemetry from games Drachen et al. (2013b); Weber et al. (2011); Feng et al. (2007).

Profiling users has emerged across multiple data science application areas as a way of managing complex user data, and to discover underlying patterns in the behavior of the player base. Profiling users allow for a condensation and modeling of a complex behavioral space. Profiles allows us to consider players in a non-abstract, quantifiable way, building an understanding about who the players are and how they will play, or are playing, the game or games being investigated.

Player profiling has been performed for a variety of different reasons and based on similarly varied methodologies, from work focused on customer profiling, psychological modelling, cohort analysis and more. In this chapter, the focus is on behavior profiling based on telemetry data. With this is meant models of player behavior that are generated exclusively based on telemetry data obtained from logs of player behavior, either during gameplay or in relation to it. Telemetry-driven profiling is one of the central challenges in game analytics, and is focused on condensing varied, high-volume and often volatile data into descriptions that highlight the patterns in player behavior Drachen et al. (2013b); Bohannon (2010); Drachen et al. (2013a); Yannakakis and Togelius (2015); Drachen et al. (2014a); Drachen and Schubert (2013); Luton (2013); Drachen et al. (2012).

The idea of using customer data to inform marketing and product design has an extensive history in Information Science, where user profiling was developed to deal specifically with the problem of data overload. This is a prevalent issue in any user/customer-focused industry today, and certainly so in games. In games, we easily extract dozens to hundreds of features from direct user-game interaction, and supplement these with data from marketing, attribution, playtesting, social networks and more. To makes things even more challenging, data are usually collected from

large numbers of players, from potentially long-term interaction periods and are typically temporally volatile Bauckhage et al. (2015).

Despite these challenges, behavioral profiling plays an important role in game analytics. However, the general application of analytical principles to large-scale behavioral data in games is still relatively short and has a fragmented history. Behavioral profiling in games originate in game design and game AI Drachen et al. (2013b); Mellon (2009); Zoeller (2011); Bohannon (2010), and work in these areas has been varied out for over two decades. However, with the recent introduction of large-scale behavioral tracking in online environments and games in particular, accompanied by the emergence of non-retail based business models, new data sources has led to a proliferation of work focusing on pattern-finding and -definition in the behavior of players. For example, focusing on playstyles, strategies, prediction, profiling, etc. Drachen and Schubert (2013); bar (n.d.); Miller and Crowcroft (2010); Nozhnin (2012, 2013); Hadiji et al. (2014).

The purposes of telemetry-driven profiling can be many, from design evaluation, progression analysis, AI/bot behavior generation, monetization, user experience evaluation, and even purely explorative. Jointly, profiling helps build an understanding of the users. However, behavioral profiling in digital games is not a straight-forward task due to the common high-dimensionality in the data and the lack of clear guidelines for which types of behavioral features to incorporate into profiles. There is also a human element in the decision-making processes which has a direct impact on the relative strength and applicability of behavioral profiles Drachen et al. (2013b).

These problems are perhaps especially present in games where players have wide degrees of freedom in how they want to approach and play the games, for example Massively Multiplayer Online Games (MMOGs), Open-World Games (OWGs) (also referred to as "sandbox" games due to their design) and some action-adventure games. Persistent, online games featuring large virtual environments and broad player affordances can be particularly challenging due to the high-dimensional nature of the behavioral features that can be needed for behavioral profiling. Examples include games such as *The Elder Scrolls: Skyrim*, *World of Warcraft*, *Minecraft* and *EVE Online*.

### 1.1.1 Overview of This Chapter

In this chapter the background of user profiling in games will be outlined, and a review of the current state-of-the-art presented. Furthermore, we present a number of case studies showcasing different profiling techniques and approaches, providing the first overview of the topic and a reference for future work in the domain.

Section 1.2 provides a brief introduction to the domain of player profiling and introduces core concepts. Sections 1.3 and 1.4 reviews and analyses the current state-of-the-art of knowledge in behavior profiling in games, across academia and industry. Section 1.5-1.8 provides case examples and in-depth discussion about different techniques for telemetry-driven profiling. Finally, Section 1.9 assembles the various threads and summarizes the current status of profiling within the domain of game analytics highlighting future research directions.

## 1.2 Player Profiling: an Introduction

Behavioral profiling in games provides the ability to consider the users in a non-abstract, quantifiable way. Profiling techniques essentially condense the behavioral space so any patterns can be located, or hypotheses tested. Following definition, profiles need to be refined into a format that permits action to be taken on them by the stakeholder on the receiving end. For example, for a level designer, profiles could be descriptions of how players overcome a specific challenge in a game, with clear indications as to where things to right and wrong.

In games, there are typically two overall goals with player profiling: 1) Correlational: To correlate profiles with specific behaviors such as game completion potential, user experience, monetization, churn, retention, cross-game transportation, cross-promotion, social influence, etc. 2) Inferential: To investigate how and why specific behaviors occur as a function of user traits and/or behaviors.

We can also consider how profiles are developed, usually either bottom-up or top-down. The former is explorative, focused on locating patterns we did not know existed. This approach is useful as soon as data is available, e.g. a prototype. Bottom-up profiling is usually feature intensive. Top-down profiling focuses on testing hypotheses, e.g. how valid already established profiles are given a new player cohort. This approach is typ-



Figure 1.1 Current work on behavioral profiling in games can be divided into five categories depending on the overall purpose of the analysis: snapshot, dynamic, predictive, psychological and spatio-temporal profiling. Each category targets specific aspects, dimensions or properties of player behavior in games.

ically employed late in production and during the live period of a game, notably for consistency-testing and updating previously defined profiles.

Profiles can be generated either to target individual or groups of players. Individual profiles seek to discover characteristics of specific people, and is based on data from only that person. Group profiling, which is the most common due to the typical large number of players involved in analysis (see e.g. Drachen et al. (2013b, 2012)), tries to categorize individuals as a kind of individual – i.e. a type or group. Group profiling is less precise than individual profiling but often required in practice to manage high-dimensionality datasets. Every group profile will have a *fit* which is the quality of the profile in terms of what it is applied to. Fit is an important component to integrate when considering how to distribute players into profiles, or taking action on players who fall into specific profiles Sifa et al. (2013); Mahlmann et al. (2010); Drachen et al. (2009). If a profile is 100% distributive it means that all properties applies fully to everyone in a group, e.g. *all bachelors are unmarried*. In practice, analytically generated group profiles are non-distributive to a greater or lesser degree – and often the latter Drachen et al. (2012). This is a key concern when considering how to act on profiles in an industrial or academic context. In general, the more detailed we try to make

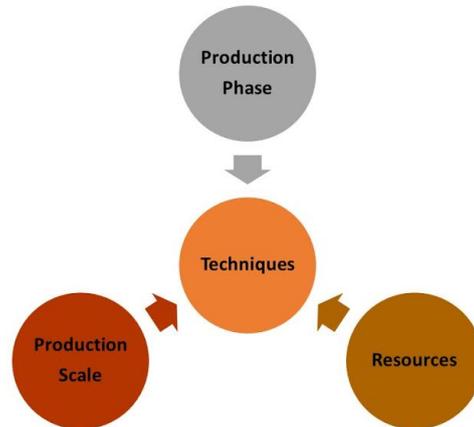


Figure 1.2 The techniques available for behavioral profiling in games rests on a variety of factors, notably: 1) The active production phase of a game, which determines what kinds of data that are available; 2) The production scale, which determines the variety of data available, from a few key features to hundreds or more; 3) The overall level of resources dedicated to analytics in the company and the active production.

profiles, the less players they apply to, and there is definite element of cost-benefit balancing in play here.

Finally, player profiles can also be classified according to the information they are built from. Two core types are protean and player profiles Drachen (2014). The latter is based on actual behavioral, attitudinal or other data, while the former is based on theoretical models and design intent Taylor and Todd (1995); Solomon (2014); Canossa and Drachen (2009a,b). Data-driven profiles can be developed from the earliest user testing and they are ideally updated throughout production and during post-launch. Protean profiles are commonly used in game design and can be defined from day 1. Importantly they must be kept updated as a function of design changes in order to remain useful. They must also be integrated across the team to ensure coherence in their use Drachen (2014).

The process of building profiles rests on well-established guidelines for knowledge discovery in IT, irrespective of the specific algorithms or models used for pattern recognition (ranging from simple but effective tools such as cohort analysis to machine learning) Drachen et al. (2013b):

1. **Discovery:** A knowledge discovery process is performed to provide sets of correlated data for profiling, i.e. information about which patterns and correlations we see in the data. For example, that kill/death ratio appears to be important to progression in a FPS.
2. **Selection:** We decide which patterns to use and which behaviors to employ in the further work with developing profiles. For example, if we are interested in churn, we use patterns showing correlations between behavior and players leaving/staying in the game. Via experimental work we can also investigate causal relationships. Various types of machine learning algorithms can be employed to search the variance space, with clustering being a popular example.
3. **Interpretation:** In this step we define the profiles. This can be done in a variety of ways, but a sharp eye on the application is important. This is an often over-looked or under-prioritized phase leading to problems in the fourth step.
4. **Application:** This vital step involves taking action on the information contained in the profiles. This step is possibly the most difficult to execute in practice as it often involves communication between stakeholder groups that speak completely different languages. . . .

The process is ideally cyclic: Players change behavior, the composition of the population changes over time, as does game design in persistent or semi-persistent game. So profiles should be continually updated as new data become available.

It is also worth noting that profiling at all levels is not an objective process. The process relies on choices, such as the algorithm or model used, how to pre-process data, feature selection, interpretation etc. Because of these choices, there is the potential for bias and error at all of these steps Drachen et al. (2013b).

### 1.3 Related Work: Player Profiling - In the Lab and in the Wild

Behavioral profiling in games based on telemetry data is a relatively recent endeavour, distributed across a variety of subdomains and purposes within the overall confines of game research and game development, notably game analytics and game user research Bohannon (2010); El-Nasr, M. S. and Drachen, A. and Canossa, A. (2013); Fields and Cotton

(2011); Lim (2012). However, within game AI, agent modeling, adaptive games, the use of profiling for modeling autonomous entities has a history stretching over two decades, although the use of player-derived telemetry data in AI modeling is more recent Kim et al. (2008); Yannakakis (2012); Missura and Gärtner (2009); Yannakakis and Hallam (2009); Yannakakis and Togelius (2015).

Profiling players has a long history stretching back to for example the work of Bartle Bartle (n.d.), Nacke Nacke et al. (2014) and Bateman and Boon Bateman and Boon (2006), the original and newest work of Yee and Ducheneaut Yee (2014); Yee and Ducheneaut (2015), and others who used design principles, motivational and psychological theory, combined with observation and surveys, to build the first frameworks categorizing player behavior. Trying to infer player motivation, personality or similar based on in-game behavior forms an emergent key topic in game analytics, which connects Psychology, Social Science and analytics, but is not the topic of the current work.

Focusing on the use of behavioral or attitudinal data to profile players specifically, the current developments are generally driven by the recent availability of large-scale behavioral data from games, thanks to the adoption of tracking technologies and the business necessity of being able to take advantage of such data in order to remain competitive Fields and Cotton (2011); Kersting et al. (2010); Bauckhage et al. (2015); Lim and Harrell (2015).

Today, telemetry-driven behavioral profiling across industry and academia can take a variety of forms, from simple cohort analyses or segmentations of players, to machine learning-driven methods, and address a variety of goals, including design evaluation, monetization, optimization, debugging and exploration Mellon (2009); Nozhnin (2013); Bauckhage et al. (2015); Drachen et al. (2012); Yannakakis and Togelius (2015); Drachen et al. (2013b).

#### 1.4 Telemetry-driven profiling

Early work on telemetry-driven profiling originated in the industry, notably from Microsoft Studios Research who championed the adoption of telemetry in game user research Kim et al. (2008); Thompson (2007); Canossa et al. (2011). In the past few years, every major publisher in the world has added analytics competencies, not only for F2P mobile games, but across all game projects Mellon (2009); Zoeller (2011); El-Nasr et al.

(2013). The rise of F2P games has notably added to the industry's focus on behavior analysis. These are games with no up-front cost to the customer, with revenue depending on In-App Purchases (IAPs) (and sometimes associated branded products). Revenue is thus dependent on the ability of the developer to convince some portion of the customer base to purchase virtual items for real money. In order to be successful as a business model, these games require continued analysis of player behavior, and is challenged by changes in player behavior and the shifting composition of the player base Fields and Cotton (2011); Mellon (2009); Drachen et al. (2014a); Sifa et al. (2013); Luton (2013).

Academic-industry partnerships are also increasingly common in game analytics Weber et al. (2011); Hadiji et al. (2014); Runge et al. (2014); Runge (2014); Drachen et al. (2009), although there remains a general lack of knowledge- and dataset transfer due to confidentiality requirements vs. academic publishing needs.

The recency of game telemetry as a research topic also means that most available work is case-based, e.g. application of a specific algorithm to behavioral data from a specific game. However, industry work in F2P mobile games are seeing the beginnings of shared underpinnings on the types of metrics that can be used for different types of analysis, e.g. segmentation, funnel analysis and churn prediction Hadiji et al. (2014); Runge et al. (2014); Nozhnin (2012, 2013); Sifa et al. (2015b); Fields and Cotton (2011); Luton (2013); Drachen et al. (2013b).

Current work on behavioral and behavioral-attitudinal profiling in games can be categorized according to the method used, whether it is mainly descriptive, or rests on unsupervised or supervised machine learning. Machine learning techniques can for example be classified on their model complexity, their required input data, etc. However, the approach adopted here categorizes current work based on the intended application (use), because this better matches the real-use context of behavioral profiling in games. Additionally, the available literature is readily organized in this manner due to the applied focus of the work in the domain. In brief, the five categories are: snapshot, dynamic, predictive, psychological and spatio-temporal profiling. It is important to note that specific machine learning approaches such as clustering, affinity mining or prediction can be applied in one or more of these.

### 1.4.1 Snapshot profiling

Snapshot profiling is focused on developing an understanding of the patterns of behavior as they occur at the operational level. The majority of the work on telemetry-based behavior profiling in games has been based on snapshot data. The earliest work directly focusing on profiling is possibly Drachen et al. (2009), who used data from *Tomb Raider: Underworld* to generate profiles of 1365 players based on Emergent Self-Organizing Networks. Four clusters were located, encompassing over 90% of the sampled players. The profiles were expressed in game design language to enable game designers to take action on them. Around the same time, Thureau et al. (2009) applied nonnegative-matrix factorization to classify player guilds in *World of Warcraft*. The goal here was classification rather than profiling, but the results could be utilized in a similar way. This characterizes much of the research on behavioral profiling in games, i.e. that while direct player profiling is not the end goal, the results ultimately provide profiles of one kind or another that informs design, monetization, server load balancing, or other aspect of games.

This work was followed-up by Drachen et al. (2012) who built snapshot profiles of players from the MMOG *Tera Online* and *Battlefield 2*, using a variety of clustering methods. Drachen et al. (2013a) investigated four different clustering techniques in terms of how useful they were for generating interpretable behavioral profiles in games, using data from *World of Warcraft*. Drachen et al. (2014b) adopted dimensionality reduction techniques to investigate patterns in character names in *World of Warcraft*. Bauckhage & Sifa [30] presented k-maxoids, a k-means variant, and described its usefulness for clustering behavioral telemetry. The authors presented a case study of vehicle usage data from *Battlefield 3*, identifying seven clusters of behavior showcasing the preferences of players for specific vehicles in this game. Finally, Bauckhage and Sifa (2015) summarized the state-of-the-art of using clustering to analyze behavioral telemetry in games. The authors outline multiple future perspectives on behavioral profiling in games, including the application of spatio-temporal analytics.

Pattern searching of player behavior was also performed by Thawonmas & Iizuka Thawonmas and Iizuka (2008), who used frequency analysis to find behavior patterns in the MMOG *Cabal Online*, focusing specifically on bot-detection via identifying aberrant behavior. Bot-detection is a recurring topic in game analytics for MMOGs where in-

game resources represent considerable value both internally and in terms of real-world value. Focusing on the Real-Time Strategy game *StarCraft*, Weber & Mateas (2009) employed a series of classification algorithms for recognizing player strategy, employing regression in order to predict the production of units or buildings. Müller et al. (2015) classified player behavior in *MineCraft* using PCA. The focus is on the distribution of time players put into four main categories of behavior, namely building, mining, fighting and exploring. Lim & Harrel (2015) used the Archetype Analysis approach of e.g. Drachen et al. (2012) to investigate social phenomena in *Ultima IV* and; focusing on modeling identity representations in *The Elder Scrolls IV: Oblivion*. hol (n.d.) used Monte-Carlo Tree Search controlled procedural personas to simulate players in the puzzle game *MiniDungeons 2*. Normoyle & Jensen (2015) used Bayesian semi-parametric clustering to investigate choice-outcome relationships in *Battlefield 3*. Normoyle and Jensen (2015) used bayesian clustering for grouping players. Finally, Suznjevic et al. (2011) modeled player behavior in the MMOG *World of Warcraft* as a function of five different types of behaviors, exploring temporal trends. The overall aim was to contribute to the problem of predicting network traffic in MMOGs accurately.

In esports analytics (as defined by Drachen et al. (2014c)), a small number of publications have focused on clustering or profiling player behavior. Gao et al. (2013) targeted the identification of the heroes that players are controlling and the role they take. They define a basic model with three roles a player can fulfill. Eggert et al. (2015) built on the work of Gao et al. (2013), applying supervised machine learning to classify the behavior of DOTA players in terms of their hero roles or playstyles. The authors used attribute evaluation techniques to develop a series of hero roles which were then evaluated against DOTA match data. Southey et al. (2005) developed a general purpose analysis tool (SAGA-ML) to analyze metrics data from the game FIFA'99. The aim was to identify faults in the game design that permits maneuvers that can be used to repeatedly score goals.

#### 1.4.2 Dynamic profiling

Player behavior change as a function of time Fields and Cotton (2011); El-Nasr et al. (2013); Zoeller (2011); Mellon (2009); Sifa et al. (2013); Drachen et al. (2014a); Sifa et al. (2014b). Furthermore, persistent games which sees the same players interacting with a game over potentially

long temporal periods, experience a constant change in the population of players Fields and Cotton (2011); Mellon (2009); Drachen et al. (2014a); Sifa et al. (2014b). This is notably the case for F2P games, which have persistence as a key design factor in order to support the underlying business model Hadiji et al. (2014); Mellon (2009); Drachen et al. (2014a); Sifa et al. (2014b); Runge et al. (2014); Nozhnin (2012, 2013); Fields and Cotton (2011); Luton (2013); El-Nasr et al. (2013); Nozhnin (2013). Games themselves can also change over time, for example via patches, updates or expansions. These three factors jointly mean that profiles generated based on snapshot data have a limited period during which they are valid as representations of the player base. In the industry it is therefore increasingly common to see player profiles being iteratively generated as a function of set time intervals, e.g. 24 hours. While the underlying unsupervised machine learning methods are similar for snapshot and dynamic profiling, the latter are constantly regenerated and additionally permit historical viewpoints on changes in the behavior of the players (or systems), and also acts as a starting point for predictive analytics Hadiji et al. (2014); Runge et al. (2014); Nozhnin (2012, 2013); Drachen et al. (2013b).

Some of the earliest temporal analyses of player behavior originate in network analysis, e.g. Feng et al. (2007) who investigated long-term patterns in playtime and session intervals in MMORPGs. Similarly, Sifa et al. (2014b) described large-scale cross-games patterns in playtime and retention patterns for more than 3000 titles. Sifa et al. (2013) and Drachen et al. (2014a) used temporal bins in conjunction with iterative profiling to investigate the evolution of player profiles as a function of game progression and MMOG game lifetime respectively. Thawonmas et al. (2011) studied revisitations to the game or specific area of the game world in an MMOG. Nozhnin Nozhnin (2012, 2013) provided insights into the practical development of churn prediction models in game development, working with the MMOG *Aion*. Hadiji et al. (2014), Runge et al. (2014) and Sifa et al. (2015b) focused on churn prediction in F2P games, categorizing players according to whether or not they were predicted to churn and at what point. Sifa et al. (2015b) also outlined methods for predicting which players that would make IAPs. Yang and Roberts (2014) presented an approach for discovering and defining patterns in combat tactics among winning teams in the MOBA DOTA, based on graph representation. The authors attributed features to the graphs using frequent sub-graph mining which allowed them to describe how different combat tactics contributed to team success in

specific situation. Also in the area of e-sport analytics, Ong and Penge (2015) applied clustering to learn optimal team compositions for the the MOBA League of Legends. The goal was to develop descriptive play style groupings for informing a win/loss prediction model.

While predictive profiling can be as detailed and multi-dimensional as required, the currently most common techniques outside Game AI can generally be classified as delivering *shallow* profiles, i.e. profiles that are generated based on a small number of features and with a resulting binary classification such as *churner* and *non-churner* Nozhnin (2012); Hadiji et al. (2014); Runge et al. (2014). This is in contrast to *deep* profiling which categorizes or classifies players according to many features or dimensions. There is no agreed-upon boundary between these definitions, and their use depends on the context of analysis. Adapting content to players, whether for the purpose of retention, monetization, experience or learning, is generally aided by a more detailed categorization of the players which provides information about their specific behavior, and ideally the kinds of challenges they encounter in progressing in the game, making in-game social connections, accomplishing goals, etc. Sifa et al. (2015b); Hadiji et al. (2014); Runge et al. (2014)

Prediction has a less marked role beyond the F2P game context, but is also finding use to predict player navigation in 3D environments, predict how far specific players will get into a game, predicting what kind of problems specific players will encounter, etc. The vast majority of the current knowledge about these application areas rests within the industry and is only generally available through industry talks and presentations. Game AI should again be mentioned as a domain where predictive behavioral models have been a focus of work for e.g. guiding bot behavior Bauckhage et al. (2006); Bauckhage and Thurau (2004).

The problems associated with imbalanced datasets are of direct importance in predictive profiling in F2P games. This is not a unique problem for games Chawla et al. (2002), but F2P games form a situation that is different from subscription-based or retail-based business models (and outside of games entirely, e.g. retail). Firstly, F2P games follow a freemium model, which means that the lifecycle of these games is different from non-freemium situations. Secondly, F2P games do not change as a function of a purchase. As noted by Sifa et al. (2015b), installing a F2P game is not a commitment at the same level as buying a product in advance and this is one of the main reasons for the imbalance issue. For more information on how to deal with imbalance issues in behavioral

telemetry, see e.g. Sifa et al. (2015b); Hadiji et al. (2014); Runge et al. (2014); Nozhnin (2012, 2013).

Another important problem in predictive profiling is the determination of the right model input features. There is relatively little publicly available knowledge on this issue, but e.g. Sifa et al. (2015b); Hadiji et al. (2014); Runge et al. (2014); Nozhnin (2012, 2013); Drachen et al. (2013b); Feng et al. (2007); Sifa et al. (2014b) discusses this problem in more detail.

### 1.4.3 Spatio-temporal profiling

All games contain spatial and temporal elements, whether digital or non-digital. Especially in 3D digital games, the spatial dimension is often important to the perceived experience of the game. Furthermore, spatial navigation and positioning are key gameplay elements in games such as First-Person Shooters and many multi-player games Drachen and Schubert (2013). A number of approaches for e.g. trajectory analysis and –classification have been adapted for use in Game AI and in Game Analytics, used e.g. to detect illegal bot programs, study player tactics or to train AI bots. Behavioral analysis can be carried out without considering the temporal and spatial dimensions of play (these are referred to as Static analysis), however, it is often necessary to include one or more of these in order to build the required insights. Snapshot profiling can be done without historical or spatial data, whereas dynamic profiling invariably ends up providing temporal patterns. Similarly, predictive modeling requires temporal information. Neither profiling approach requires spatial information, however. Spatial behavioral data are usually only included when needed given the purpose of the analysis. Additionally, spatio-temporal game analytics can be cumbersome and require that interpretation is performed in relation to the actual virtual environment. Ignoring this step in the analysis cycle lead to the risk of misinterpretation of the root causes of the observed behaviors Drachen and Schubert (2013).

While a full overview of the literature is out of scope here, due to the sheer variety of applications of spatio-temporal behavioral data in Game AI and Game Analytics, a few key publications are briefly discussed here. Firstly, Drachen & Schubert Drachen and Schubert (2013) provide a relatively recent overview of spatial and spatio-temporal game analytics. The use of spatio-temporal telemetry for visualizing player behavior originates about a decade back, for example with the work

of Hoobler et al. (2004) on the multi-player First-Person Shooter Return to Castle Wolfenstein. Drachen and Canossa (2009) applied Geographic Information Systems to characterize player behavior in games, focusing on Tomb Raider: Underworld. The work was expanded to include e.g. overlay analysis by Drachen and Canossa (n.d.). Miller and Crowcroft (2010) investigated group movement in the Arathi Basin battleground of World of Warcraft, grouping trajectories of player based on waypoint modeling. Bauckhage et al. (2014) adopted DEDICOM to not only cluster players of Quake Arena based on their in-game behavior, but also develop directional waypoint graphs for behavior-based partitioning of game environments. Within es-ports, Drachen et al. (2014c) investigated skill-based differences in the behavior of DOTA players. Finally, Rioult et al. (2014) used topological measures in the same game to investigate player positioning and the influence of this on predicting match outcomes. Campbell et al. (2015) presented work on path clustering of player trails.

#### 1.4.4 Psychological Profiling

As mentioned above, telemetry data are only one source of information about players, and a relatively recently introduced one at that. While the focus here is on telemetry-driven approaches, it should be mentioned that behavioral profiling has an extended history based on information derived from user-testing, surveys, marketing data, etc., and has there given rise to the concept of Psychographic customer modeling Raghu et al. (2001). With the work of Bartle (n.d.) and others, the idea of tying in observations from gameplay to profiling, or use gameplay behavior as the sole basis for profiling, was introduced. Initially such models were based on observation only. In the early 2000s authors such as Bateman and Boon (2006), Ryan et al. (2006), Nacke et al. (2014) and Yee and Ducheneaut (2014); Yee and Ducheneaut (2015) began using online surveys to build profiles based on the motivations/needs or personalities of players, however, these were not initially tied to in-game telemetry but the perceptions of the players themselves about their in-game behavior and motivations driving these. In recent years, the idea of using telemetry data to draw inferences about player psychology has emerged, with however only early work having been done so far.

For example, van Lankveld et al. (2011) used a custom module from

*Neverwinter Nights* generated using the AURORA engine to investigate correlations between player behavior and the Five Factor Model of personality, measured using the NEO-PI-R questionnaire. The experimental work indicated that it was possible correlating at least some aspects of the five personality traits in the model and in-game behavior. In follow-up work, Spronck et al. (2012) investigated whether the same relationships were present in *Fallout 3*, measuring personality traits using the NEO-FFI survey this time. The results generally supported the previous work, although sample sizes this time also were understandably small given the laboratory-based nature of the work. Canossa et al. (2013) triangulated behavioral telemetry from *MineCraft* with the Reiss Motivation Profiler serving as a hermeneutic grid. Canossa et al. (2013) investigated correlations between in-game behavior in *Kane & Lynch: Dog Days* and player frustration in a mixed-methods study.

Psychological profiling based on behavioral telemetry remains in its infancy. It is unknown what the state-of-the-art of these methods is within the industry due to confidentiality requirements. It is possibly a near-future major new topic in game analytics, as there is an obvious interest in tying in-game behavior with player psychology, as this provides the basis for marketing that targets the specific interests of the players, as well as for adaptive games that modify themselves to the inferred motivations and personalities of the players (Yannakakis and Togelius (2015); Yannakakis (2012)). Finally, this perspective is important in learning games, where the motivation to engage with teaching material is crucial.

## 1.5 Snapshot Profiling In Games

Typically the data used for snapshot profiling consists of aggregate metrics about the players and/or their behavior. Generally, historical data is not used but rather information about the state of the players at the present. Typical examples include dimensionality reduction of high-variety datasets about player characters in Massively Multi-Player Online Games (MMOGs) or other online multi-player games, in order to obtain an understanding about the composition of the current player base (Gao et al. (2013); Feng et al. (2007); Bauckhage and Sifa (2015); Drachen et al. (2012)). Although there are various methods that can be used for this task, the usually preferred methods for snapshot-profiling in the game industry are based on manual segmentation using predefined

features Bauckhage et al. (2015). These methods usually do not capture the interesting patterns that are related to relationships with datasets. However, statistical machine learning tools here not only help us find interesting patterns but also give us the possibility to identify important features. For the task of profiling in this section we will start with snapshot profiling, which is commonly the first level of profiling performed for multi-dimensional behavioral datasets. For the sake of generality we will continue this section with explaining the theoretical foundations of one of the mostly used algorithms for snapshot profiling and a profiling case study from Sifa et al. (2015a) covering a large scale playtime based analysis of millions of players.

### 1.5.1 $k$ -means Clustering

The simplicity of its derivation and implementation has made the  $k$ -means algorithm arguably one of the most popular (clustering) procedure in data science Wu et al. (2008) and specifically in game analytics to find central behavioral clusters Bauckhage et al. (2015); Drachen et al. (2012); Bauckhage and Sifa (2015). The main objective of  $k$ -means algorithm is to group a given set of data points under a predefined number of clusters. Formally given  $k \in \mathbb{N}$  and a set of arbitrary dimensional data points  $X = \{\mathbf{x}_i \in \mathbb{R}^m \mid i = 1, \dots, n\}$ , the  $k$ -means algorithm finds appropriate centroids  $Z = \{\mathbf{z}_i \in \mathbb{R}^m \mid i = 1, \dots, k\}$  by minimizing

$$\min_{\mathbf{z}_i} E(k) = \sum_{i=1}^k \sum_{\mathbf{x}_j \in C_i} \|\mathbf{x}_j - \mathbf{z}_i\|^2. \quad (1.1)$$

The algorithm randomly initializes the centroids and determines the clusters as

$$C_i = \{\mathbf{x}_j \in X \mid \|\mathbf{x}_j - \mathbf{z}_i\| \leq \|\mathbf{x}_j - \mathbf{z}_l\| \forall l \neq i\}. \quad (1.2)$$

After that each new cluster will be updated as being the center of the assigned points by

$$\mathbf{z}_i = \frac{1}{|C_i|} \sum_{\mathbf{x}_j \in C_i} \mathbf{x}_j. \quad (1.3)$$

Repeating the (1.2) and (1.3) until convergence will yield the optimal centroids. Additionally, the problem can be cast as a constrained matrix factorization problem as in Bauckhage (2015).

### 1.5.2 Case Study: Cross Game Player Profiling

Now we turn our attention to a snapshot profiling study that is conducted by Sifa et al. (2015a) aiming to reveal how players distribute their time playing particular games. The study we present here is the first part of the player based analysis that is presented in Sifa et al. (2015a). Having analyzed the time six million players (of a multi-game social networking platform called *Steam*) spent on more than 3007 games using  $k$ -means clustering, the authors found 11 different behavioral profiles and reported more than half of the players are *specialized* in one particular game. Tbl. 1.1 shows the summarized results from Sifa et al. (2015a) where the profiles are described in terms of their representation ratio and characteristics. The results indicate inclinations of game preferences with respect to particular titles or set of titles (such as *Team Fortress 2* (TF-2) players or *Counter Strike*(CS) series) or to particular game genres such as first person shooter (FPS) game players in general. For more details of the types of methods used to select the profiling parameters and the dataset we refer the reader to Sifa et al. (2015a). These types of insights help, the analysts reveal interesting player behaviors giving additionally a first impression about the dataset at hand for further analysis such as spatio-temporal profiling, which will be explained in the next sections.

game TF 2 and Garry's Mod for most of their playtime.

## 1.6 Dynamic Profiling with Extremes

Considering the cases of dynamic player profiling, it is vital to know the coverage of the existing data to provide meaningful and actionable insights to the designers and the developers for decision making Bauckhage and Sifa (2015). In this context, Archetypal Analysis plays an important role owing to its unique structure. It not only reveals extreme behavioral basis vectors that are easy to interpret, but also allows for soft clustering through the stochastic belongingness coefficients. In the following we give an introduction to Archetypal Analysis that includes its matrix factorization formalization as well as approaches to find the archetypes. Following that we present a case study covering level-wise profiling of players of an action-adventure game.

Profile Identifiers	Ratio	Characteristics
Customizers	3.1	Valve's flagship customization game TF-2 and Garry's Mod
DOTA 2	9.7	Typical <i>DOTA-only</i> players
FPS	5.2	Played only famous FPS games: CS:Source, CoD and TF-2
Left 4 Dead 2	0.8	FPS players with a heavy emphasis on Left 4 Dead 1 and 2
CS: Source	8.6	Playing mostly CS:Source
Counter-Strike Original	10.6	Player of the original CS game
Civilization V	1.0	Sid Meier's Civilization V players
Active Steam Players	38.8	Played variety of games across different genres nearly equal amount of time
Balanced DOTA 2	5.4	DOTA2 players that are more inclined to play other games
TF-2	15.6	Mostly played TF-2
Counter-Strike Alternative	1.2	CS Condition Zero and original CS players

Table 1.1 *Snapshot profiling results from gameplay distributions of six million million players. Results are from Sifa et al. (2015a)*

### 1.6.1 Archetypal Analysis

Introduced in Cutler and Breiman (1994), Archetypal Analysis is soft clustering method based on representing data entities with respect to archetypes which are defined to be extreme data points. Formally, given a data matrix  $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n] \in \mathbb{R}^{m \times n}$  and an integer  $k$  s.t.  $k \ll n$  archetypal analysis performs the following factorization:

$$\mathbf{X} \approx \mathbf{ZH} = \mathbf{XBH} \quad (1.4)$$

, where  $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_k] \in \mathbb{R}^{m \times k}$  contains the  $k$  archetypes,  $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_k] \in \mathbb{R}^{k \times n}$  contains the stochastic belongingness coefficient vectors for each datapoint to the archetypes and  $\mathbf{B} = [\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_k] \in \mathbb{R}^{n \times k}$  contains the stochastic coefficient vectors to represent the archetypes as a convex mixture of actual data points. After calculating the archetypes and coefficient matrices, a data point  $\mathbf{x}_i$  can be represented as

$$\mathbf{x}_i \approx \mathbf{Zh}_i = \sum_{j=1}^k \mathbf{z}_j h_{ji} = \sum_{j=1}^k \sum_{p=1}^n \mathbf{x}_p b_{pj} h_{ji}. \quad (1.5)$$

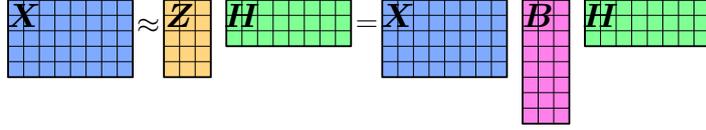


Figure 1.3 A pictorial representation of *Archetypal Analysis*. The data matrix  $\mathbf{X} \in \mathbb{R}^{m \times n}$  is factorized into  $\mathbf{Z} \in \mathbb{R}^{m \times k}$  which the matrix of archetypes and a belongingness matrix  $\mathbf{H} \in \mathbb{R}^{k \times n}$  which is column stochastic. When representing the archetypes as a convex combination of actual data points a further column stochastic matrix  $\mathbf{B} \in \mathbb{R}^{n \times k}$  is also introduced.

As a matrix norm minimization problem finding appropriate archetypes can be formally presented as minimizing the residual sum of squares

$$\min_{\mathbf{A}, \mathbf{B}} RSS = \left\| \mathbf{X} - \mathbf{X}\mathbf{B}\mathbf{H} \right\|^2 \quad (1.6)$$

with the following constraints

$$b_{ij} \geq 0 \wedge \sum_{i=1}^n b_{ij} = 1 \wedge h_{ji} \geq 0 \wedge \sum_{j=1}^k h_{ji} = 1. \quad (1.7)$$

Numerous approaches have been proposed for finding  $\mathbf{H}$  and  $\mathbf{B}$  minimizing (1.6) Bauckhage and Thureau (2009); Morup and Hansen (2012); Thureau et al. (2010); Sifa et al. (2014b); Kersting et al. (2010). The first algorithm proposed by Cutler and Breiman (1994) aimed to solve convex least squares problems to find archetypes and its coefficients. To handle large datasets the method has been modified as an active set approach by Bauckhage and Thureau (2009). A distance geometry based approach, called Simplex Volume Maximization (SIVM) has been introduced by Thureau et al. (2010) showing the relation between increasing the volume of the data simplex and reduction of error in (1.6). By constraining the archetypes to be actual data points, i.e. constraining  $\mathbf{B}$  to be a sparse and non-overlapping binary matrix, SIVM first finds the data-points that maximize the Cayley-Menger determinant as being the archetypes and finds the appropriate belongingness coefficients  $\mathbf{H}$  by solving (1.6) with fixed  $\mathbf{B}$  Thureau et al. (2010). Furthermore, a formalization of finding archetypes and coefficients as gradient descent optimization has been shown by Morup and Hansen (2012) which also allows for capturing nonlinearity though kernelization Bauckhage and Thureau (2009); Morup and Hansen (2012); Sifa et al. (2014b).

### 1.6.2 Case Study: Level-wise Player Profiling In an Action-adventure Game

In order to have a picture about how archetypal analysis perform, we present a case study from Sifa et al. (2013) that is based on an analysis of 62000 players of a AAA-level jump and run game called Tomb Raider Underworld(TRU). TRU offers a third-person level oriented adventure and platformer-type game-play where the player controls a fictional character and protagonist Lara Croft. Together the storyline and a skip-pable prologue the game offers its players nearly two hundred puzzles to solve Sifa et al. (2013). The main concentration of the case study is to observe behavioral profiles and their evolution throughout the level progression using Archetypal Analysis to help designers and developers understand the players interact with the game and progress. At this stage game and task specific feature selection plays an important role to be able to build actionable profiles Sifa et al. (2013). Namely, considering the highly granular datasets (such as the one analyzed in this case study) and the level of analysis needed, aggregating variety of features help the designers to have an overall idea about how the players are interacting complex spaces. For that reason the authors in Sifa et al. (2013) extracted gameplay, playtime and interaction based features that are listed as follows:

- **Playing time:** The aggregated time of the player spent playing the game which is also analyzed population-wise in Bauckhage et al. (2012).
- **Player death:** Represents the total number of deaths of a player which can have variety of causes and depend on activity distribution of the player
- **Help-on-Demand:** Frequency of requests through the Help-on-Demand (HOD) system that provides hints and answers to solve puzzles
- **Causes of death:** The frequencies of main causes of deaths in the games that are categorized under four groups: deaths caused by melee enemies, ranged weapons, environmental factors (e.g. fire or traps) and falling.
- **Adrenaline Used:** Represents the number of used Adrenaline type attacks used allowing the player to lock to the enemies and hit them.
- **Rewards:** Numbers of ancient artifacts, shards and relics collected by the player.
- **Setting changes:** Represents the number and type of personalization based game features that the player has performed. The players

adjustments can be performed under carryable ammo, hit points of non-player characters (NPC) and the players themselves and the recovery time for jumping.

Having identified the features and represented  $\mathbf{X}$  as being the data matrix to be analyzed, Sifa et al. (2013) used SIVM to extract behavioral profiles. It is important to note that the basis vectors that are used to describe the profiles are actual players with extreme behavior which gives the ability to the designer not only to interpret the results but also to understand how extreme the players might be Bauckhage and Sifa (2015). The profiling results of running SIVM with six archetypes and their characterization are listed as follows:

- **Level 1:** Having the highest playtime among the profiles, the most populated profile contains over 76% of the players that have low death rates that are caused mainly by falling damage. are characterized by having. the profile also indicates finding many rewards (SLOW archetype). 10% of the players are characterized by low completion time, minimal use of the HOD system but a lot of death events, notably from falling and environmental causes, and also very high reward scores. Among the remaining four archetypes, making use of the savings adjustment system is common.
- **Level 2:** For the second level in TRU, the players are more divided across the six archetypes, showing a higher overall diversity in play styles. 45% of the players are characterized by low completion rates but heavy use of the HOD system (HODUSE profile), indicating some trouble with the puzzles in the game for this cluster - notably because remaining archetypes do not use the HOD system. These players complete the level quickly and die very little. 26% of the players exhibit slow completion times and high reward rates, with limited deaths. This profile was also evident in level 1 (SLOW archetype), but is much less frequent in level 2 indicating greater diversification of play styles. 21% of the players exhibit the same quick completion rate as the first cluster described, but do not use the HOD system and - maybe as a consequence - die a lot (the most of any of the clusters), mainly from falling. Perhaps this indicates a group of players who have trouble with the jumping mechanic in TRU.
- **Level 3:** The third level sees players falling into one large cluster (75%) characterized by having the longest completion time, high rewards and low death counts (SLOW archetype). This cluster was also prevalent in Level 1 and formed a smaller component in level 2. 11%

fall into a profile exhibiting faster completion times, but also heavy use of the HOD system and more deaths than the main cluster. This pattern is reminiscent to the largest cluster in Level 2. Two smaller clusters are characterized by (4%) high use of the adrenalin feature, quick completion and high reward scores, but also fairly high death scores, mainly from falling; (6%) fall into a cluster characterized by high death scores and their deaths mainly being from ranged enemies.

- **Level 4:** Similar to level 2, players form three main clusters. The mostly populated cluster here is the SLOW archetype covering 46% of the players. 24% of the players fall into the profile with large number of deaths by mostly ranged weapons and fast level completion whereas the 11.6% of the players frequently use the HOD system, obtained high scores through rewards and have high number of deaths caused by the environment and falling. 9% of the players are described as having fast completion times and high frequency of deaths through melee and ranged enemies which characterizes the players as good navigators that are challenged by movable enemies Sifa et al. (2013).
- **Level 5:** In this level the overall picture painted by the six archetypes changes. At this point there are only about 12,000 players out of the original 62,000 who have reached it this far into the game. One cluster dominates (89%), characterized by heavy use of the HOD system (HODUSE profile), but otherwise rapid completion and low deaths indicating highly skilled play but either not caring about or having trouble with the puzzles in the level. The second biggest cluster, just shy of 7% of the players, are characterized by not using the HOD system heavily, but contrarily dying a lot, and mainly from falling.
- **Level 6:** Sees a return to a more diversified profile in the archetypes. 55% are characterized by very quick completion rates, limited use of the adrenalin feature but using the savings grab adjustment heavily. This is in tune with the levels design which features many difficult jumps. Remaining clusters do not use the the savings grab adjustment. 21% of the players similarly complete the level fast, die mainly from environmental causes and use the HOD system heavily and are reminiscent of the HODUSE profile identified in previous levels, although there are some variations across the levels (as would be expected given the variations in the design of these, notably the increasing difficulty). Finally, 11% fit the SLOW profile which also appears to occur in all the levels.
- **Level 7:** 55% fit the overall characteristics of the SLOW profile (slow completion time, low deaths, high reward scores). 24% are charac-

terized by rapid completion times and overall low scores, including few rewards found, but a return to using the savings changes in the game which are otherwise concentrated on the first two levels of the game. 11% are characterized by having high death scores, from diverse causes, but rapid completion, zero use of the HOD system and high reward scores. This profile to some degree fits the five smallest of the clusters in Level 7, with some individual variations, e.g. heavy use of the adrenalin feature or use of the savings changes. But they are all generally characterized by highly skilled play, which is to be expected perhaps given that there are now only one sixth of the players left at this point in the game.

It is important to note that the results above are one of the three analysis performed for profiling the TRU players. A more detailed insights regarding playtime and level based profiling through archetypal analysis can be found in Sifa et al. (2013). In this section we have seen how Archetypal Analysis can reduce the dimensionality by yielding representative players for the profiling players in complex and high dimensional datasets.

## 1.7 Predictive Profiling in Freemium Games

Predictive profiling changes the focus from the above unsupervised approaches to supervised techniques. Predicting player behaviour is one of the central and most common challenges in game analytics, notably due to the mobile F2P section of the game industry being to a degree dependent on predictive modelling to be able to monitor, control and forecast their revenue flow. In F2P games, which operate under the freemium business model, only a small fraction of the people starting the game turn into long-term players, social network enablers and/or buyers of in-game content. Given this imbalance, the ability to predict who these players are is therefore important as it enables an optimization of Customer Relationship Management (CRM), and tailoring game content to the specific profiles of these users Sifa et al. (2015b); Hadiji et al. (2014); Runge et al. (2014); Xie et al. (2015).

### 1.7.1 Decision Trees and Random Forests

An important aspect of all game analytics work is that the results need to be described in such a way that the relevant stakeholder can act

on them, e.g. a game designer, system designer, marketer, community specialist, manager, producer or even an artist. Predictive models should therefore ideally have relatively transparent models in addition to being accurate. Decision trees are broadly used for predicting player behavior for this reason Drachen et al. (2013b); Sifa et al. (2015b); Weber and Mateas (2009).

An example of the use of decision trees for prediction was presented by Mahlmann et al. (2010), who employed 11 behavioral features as well as player progress in *Tomb Raider: Underworld*, to investigate patterns in said progress. The authors describe for example how time spent on a specific level early in the game combined with finding few hidden rewards led to a tree branch that ultimately predicted players would leave the game relatively early. Conversely, completing the early level relatively fast meant players were predicted to be retained until the later levels in the game. Decision tree-based models like these can be employed on a wide variety of behavioral variables in order to determine which that are the most important to predict a specific behavior.

Decision trees, irrespective of the specific variant, uses a graphic approach to compare alternative explanations, and assigns value to these alternatives, describing problems in terms of sequential decisions. This perspective fits the perspective of the player progressing through a game well. Given the range of models available, decision trees are also relatively powerful analytically, and robust within a range of data types and levels of measurement Rokach and Maimon (2008).

Formally, decision trees are greedy split-based learning methods that are realized in divide and conquer manner Breiman (2001); Quinlan (1996). Given an input and output space that are denoted by  $H$  and  $D$  respectively, decision trees to learn a function  $f : H \rightarrow D$ . For profiling players, we usually define  $H$  to be the space formed by the accumulated behavioral features and  $D$  to be the target variable such as the binary indicator for churning or numeric value for number of purchases Sifa et al. (2015b); Hadiji et al. (2014); Runge et al. (2014). Considering the structure of the decision tree models, they usually contain two atomic entities: *conditional nodes* which are steering the search direction with respect to the condition they entail and *leaf nodes* that contain the conclusion, i.e., the classification results. The models are learned by splitting the training data based on particular attributes into chunks that minimize a given error. While this error is usually task specific, it is usually defined as the heterogeneity (or impurity) for binary classification. For classification tasks, heterogeneity measures yield how uncertain, or mixed, a

particular split is and can be quantified using the *Gini Impurity Index*. For binary classification, given a node  $q$  as a collection of some data entities, its Gini Impurity Index is given as:

$$\text{gini}(q) = 1 - P(q = \textit{True})^2 - P(q = \textit{False})^2, \quad (1.8)$$

where  $P(q = \textit{True})$  and  $P(q = \textit{False})$  indicate the probability of entities in  $q$  belonging to *True* or *False* classes respectively. The splitting works recursively until all data entities are perfectly separated with respect to the classes or a predefined tree depth is reached. The stopping conditions can also be restricted by setting a threshold on the minimum number of elements in the leaves. It is important to note that the stopping condition directly affects the overall generalization of the learned function. Perfectly grown trees learn the training data with zero error, however, do not necessarily perform well on unseen entities. In machine learning and statistics, this is called *overfitting*. For decision trees, this can be prevented, for instance, by pruning the trees. For more information on avoiding overfitting in the context of decision tree learning using tree-pruning, we refer the reader to Mitchell (1997).

Another method to reduce the chances of overfitting has been proposed in Breiman (2001), which uses an ensemble of decision trees called *Random Forests*. The main idea lying behind Random Forests is to incorporate randomness with sampling and tree construction to obtain numerous trees that reduce the variance towards finding the actual underlying function that is learned. Using the above terminology, the trees are constructed as follows: (1) we generate  $l \in \mathbb{N}$  data samples by selecting data entities *with replacement* (a.k.a. bootstrap samples), (2) for each data sample we train decision trees using the particular sample *with randomly selected*  $c \in \mathbb{N}$  features, (3) for each new entity to classify we feed the input to all of the learned trees and combine the output, for instance, by majority voting of the class labels or averaging the resulting probabilities.

### 1.7.2 Case Study: Prediction Profiling through Purchase Decision and Churn in F2P Mobile Games

Predictive profiling plays a major role in the product development of any F2P game for resource planning. For example, estimating player retention behavior might help find critical players that are about to quit and Runge et al. (2014). We now present a combined case study for predictive profiling in mobile F2P gaming environments that is based on

the churn analysis from Hadiji et al. (2014) and purchase decision analysis from Sifa et al. (2015b) where both consider a decision tree based approach. The main aim here is to predict future player activities given player's meta data and their historical activities. Even though profiling was not the main objective of the both studies, using decision tree models provides a supervised profiling framework that can also handle nominal attributes such as country or flags indicating particular activities. That is analyzing the selected features that increase the information gain from the learnt tree or set of trees provide us useful insights about the important features to consider that lead the people to left the game or purchase in game items Hadiji et al. (2014); Sifa et al. (2015b). In both work, authors considered features that are general and mostly game independent such as *number of sessions played* or *the current absence time till the decision date* for applicability to other games. Additionally, to capture the temporal trends in changes of some important behavioral features such as playtime Hadiji et al. (2014) used parameters of a playtime model as features whereas Sifa et al. (2015b) used the correlation and deviation in time. We group the full list of features used for this case study under the type of analysis in the following.

- **Churn Prediction:** Number of sessions, number of purchases, average playtime per session, average spending per session, premium user flag, number of days, retention value, predefined spending category, average time between sessions, parameters of the playtime model, current absence time.
- **Purchase Decision Prediction:** Country, device, move count, active opponents, logins & game rounds, skill level, reached goals, world number, number of interactions with other users, number of purchases, amount spent, playtime, last inter-session time, last inter-login time, inter-login time distribution, inter-session time distribution, correlation on time, mean and deviation on time, country segments.

Starting with the churn prediction analysis, Hadiji et al. (2014) performed two types of data generation procedure to train their models. The first type of the data generation model analyzed only the churned players up to a cut off date by assigning their complete profile as churning and generated randomly sampled non-churning (synthetic) examples to train a player churn classifier. On the other hand the second data generation type introduced the notion of *soft churn window* to simulate real world applications, where players were considered churning or not churning based on their appearance in a predefined time window. For more

insights about the data generation process with a pictorial illustration we refer the reader to Hadji et al. (2014). In the following we analyze the results from the latter data generation type as it aligns with the purchase decision prediction study as well. Having built decision tree based binary classification models for players of five different F2P mobile games the authors found that average time between sessions plays the most important role in players' upcoming departure. Namely as also indicated in Feng et al. (2007) for multiplayer game players, the decision tree model trained to predict churn has also found that an increase in the time between sessions results in player's quitting the game. Other important features found to be affecting the departure of the players were number of sessions, current absence time, number of days and the predefined spending category of the players.

Moving on with the purchase prediction decision analysis from Sifa et al. (2015b), the authors considered a decision tree learning based prediction approach in which given history of player activities, they predict whether an upcoming purchase will be made and if so its quantity. They modeled the former as a binary classification problem and the latter as a regression problem. In this section we will explain the former as it built on the churn analysis from above. For this task the authors consider three supervised learning models which included decision trees, random forests and support vector machines for three observation windows of length 1,3, and 7 days. Additionally, it is important to note that the game analyzed in this study was of freemium type and the objective defining the information gain here was whether the player will have made a purchase or not. These caused a highly imbalanced class distribution where the majority of the players were non-paying users which made the prediction of paying users really difficult. To overcome this problem, the authors created synthetic players as convex combinations of randomly selected premium players to obtain the best result with random forests. Similar to the above decision tree model for churn analysis, random forests also provide a way of determining important features for the defined objective Breiman (2001); Sifa et al. (2015b). Considering the best model trained to predict the player purchases for the seven-day window, Sifa et al. (2015b) reported that Number of Purchases and Amount Spent are the most important indicator features for further purchases. That is, players that have already spent money in games will be most likely also spend money in the future. Additionally, the authors also report the importance of the social interactions with other players and some game related features such as count of the moves and the worlds.

## 1.8 Spatiot-Temporal Profiling with DEDICOM

For many contemporary games in the market, spatio-temporal activities play an important role in user engagement. This especially becomes important for open world games that allow the user to freely navigate through the maps Bauckhage et al. (2014); Campbell et al. (2015). The areas of such game worlds are constantly growing and becoming comparable to real world in terms of scale. Examples to that include Just Cause 2 with a game map of one square kilometers in total and The Elder Scrolls V: Skyrim offers an area of 38.33 square kilometers to its players. Considering the three dimensional nature of such game environments, intelligent analysis techniques are required to provide designers important feedback with respect to behavior of the players. This feedback process is particularly vital for massively multiplayer online open world games that are gradually improved and extended based on the behavior of the players.

Regarding spatial analysis of player behavior, current methods involve the heavy use of two and three dimensional heatmaps (see examples in Fig. 1.5) that color-code the visited locations with respect to frequency appearance. The main issues of heatmaps is the lack of coverage of directional and temporal information which form the basis of movement. In order to tackle these challenges and capture the movement information, Bauckhage et al. (2014) used asymmetric matrix factorization techniques called Decomposition Into Directed Components (DEDICOM) and Decomposition Into Simple Components (DESICOM). Both of these models provide a basis to reduce the dimensionality of the high order directional datasets while preserving the temporal information. The results of the models can be used to mine hidden patterns in player trajectories and allow for comparative player analysis Bauckhage et al. (2014). In the following section we introduce DEDICOM and DESICOM partitioning models and present a case study about how such methods can be used to analyze game trace data.

### 1.8.1 DEDICOM Model

As a counterpart to the well known Principal Component Analysis (PCA) and Muti-dimensional Scaling (MDS), DEDICOM is introduced in Harshman (1978) to analyze pairwise similarities that are asymmetric by nature. Given a matrix  $\mathbf{S} \in \mathbb{R}^{n \times n}$  that represents the asymmetric relations among  $n$  objects, i.e.  $\mathbf{S} \neq \mathbf{S}^T$ , DEDICOM performs the following par-

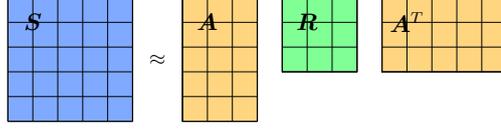


Figure 1.4 A pictorial representation of *Two Way DEDICOM* partitioning. Asymmetrical relationships given in  $\mathbf{S} \in \mathbb{R}^{n \times n}$  are decomposed in to a combination of a latent factor matrix  $\mathbf{A} \in \mathbb{R}^{n \times k}$  and an asymmetric mode transition matrix  $\mathbf{R} \in \mathbb{R}^{k \times k}$ .

tition

$$\mathbf{S} \approx \mathbf{A}\mathbf{R}\mathbf{A}^T \quad (1.9)$$

where  $\mathbf{A} \in \mathbb{R}^{n \times k}$  and  $\mathbf{R} \in \mathbb{R}^{k \times k}$ . The columns of  $\mathbf{A}$  represent the  $k$  latent factors behind the relationships encoded in  $\mathbf{S}$  and matrix  $\mathbf{R}$  encodes the relations among these latent components. DEDICOM approximates the individual relationships between two data entities  $i$  and  $j$  as:

$$s_{ij} \approx \mathbf{a}_{:i}\mathbf{R}\mathbf{a}_{:j} = \sum_{b=1}^n \left( a_{ib}\mathbf{r}_{:b} \right) \mathbf{a}_{:j} = \sum_{b=1}^n \sum_{c=1}^n a_{ib}r_{bc}a_{jc} \quad (1.10)$$

where  $\mathbf{a}_{:i}$  and  $\mathbf{a}_{:j}$  represent the  $i$ th and  $j$ th row of  $\mathbf{A}$  respectively and  $\mathbf{r}_{:b}$  represents the  $b$ th row of  $\mathbf{R}$ .

Solving DEDICOM can be cast as a problem of minimizing a matrix norm

$$\min_{\mathbf{A}, \mathbf{R}} \left\| \mathbf{S} - \mathbf{A}\mathbf{R}\mathbf{A}^T \right\|^2 \quad (1.11)$$

which is convex in  $\mathbf{R}$  but not in  $\mathbf{A}$ . This leads us to consider alternating least squares minimization procedures to find the optimal factors  $\mathbf{R}$  and  $\mathbf{A}$  minimizing (1.11) Bauckhage et al. (2014); Bader et al. (2007); Sifa et al. (2015c). Updating  $\mathbf{A}$  in a scalable fashion has been tackled by approximating the normal equations by holding  $\mathbf{A}^T$  fixed Bauckhage et al. (2014); Bader et al. (2007) or by projected gradient descent Sifa et al. (2015c). Subsequent to that, fixing  $\mathbf{A}$ , updating  $\mathbf{R}$  becomes a matrix regression problem with a close form solution Bauckhage et al. (2014); Sifa et al. (2015c); Bader et al. (2007). The resulting low rank factors can be used to reveal the hidden directional patterns and summarize the overall behavior in a compressed representation Bauckhage et al. (2014); Bader et al. (2007); Sifa et al. (2015c).

### 1.8.2 Interpretability through constraints

It is important to note that, the presence of three factors in the approximation of each factor in (1.10) might restrict the interpretation of the resulting factor matrices  $\mathbf{A}$  and  $\mathbf{R}$  to only consider the nonnegative values Sifa et al. (2015c); Kiers (1997). This becomes especially important for hard or soft clustering interpretation of the factorization requiring additional constraints on  $\mathbf{A}$  and  $\mathbf{R}$  which might increase the fitting error in (1.11) for the cost of interpretability Sifa et al. (2015c); Bauckhage et al. (2014); Kiers (1997). In the following we explain special DEDICOM based models: *Semi Nonnegative DEDICOM* constraining  $\mathbf{R}$  to be nonnegative and *DESICOM* constraining  $\mathbf{A}$  to be nonnegative and sparse.

Introduced by Sifa et al. (2015c), semi-nonnegative DEDICOM constrains the affinity matrix  $\mathbf{R}$  to be nonnegative. This becomes important when we consider only positive valued asymmetric similarity values such as counts or probabilities. Additionally, having nonnegative  $\mathbf{R}$  allows us to interpret both positive and negative loadings that are encoded in  $\mathbf{A}$  Sifa et al. (2015c). Formally, since setting the negative entities in  $\mathbf{R}$  for its update does not always guarantee the global minimum of (1.10) for fixed  $\mathbf{A}$  with nonnegativity constraint, Sifa et al. (2015c) showed how the optimization procedure for  $\mathbf{R}$  can be formalized as a nonnegative least square problem. The resulting algorithm has been shown to find hidden migration patterns among players.

Decomposition Into Simple Components (DESICOM), which is a sparsity based DEDICOM model, is introduced by Kiers (1997) to obtain interpretable (i.e. *simple*) factors. The model constrains  $\mathbf{A}$  to be row sparse, that is, each row contains only one nonnegative value while others are zero-valued. The algorithm suggested in Kiers (1997) works in alternating least squares fashion by updating each row of  $\mathbf{A}$  at a time and  $\mathbf{R}$  by matrix regression by keeping  $\mathbf{A}$  fix. Although the runtime of this algorithm is longer than the algorithms suggested to traditional DEDICOM models, DESICOM offers aspects for interpretability of the models Kiers (1997); Bauckhage et al. (2014).

The algorithm presented in Kiers (1997) minimizes the same objective function in (1.11) by simultaneously updating  $\mathbf{A}$  and  $\mathbf{R}$  by keeping the other factor matrix fixed. The difference of this algorithm to the rest of the algorithms (e.g. ones in Bauckhage et al. (2014); Sifa et al. (2015c); Bader et al. (2007)) is the update of  $\mathbf{A}$  is also done row-wise and simultaneously. Namely, by keeping the other rows fixed, each row  $\mathbf{a}_i$  can be

updated by minimizing a function that is derived from (1.11) to only depend on  $\mathbf{a}_i$ . Since we require to have only one non-negative entry in every  $\mathbf{a}_i$  and reduce the total error in (1.11), the algorithm finds the dimension  $l \in [1 \dots k]$  that yields the smallest error value, sets the value of  $a_{il}$  to the minimizer and all other values (i.e.  $m \in [1 \dots k] | m \neq l$ ) of  $\mathbf{a}_i$  to zero. The advantages of DESICOM regarding interpretability are threefold. First, the cluster assignment that is done by assigning each entity to the cluster indexed by the single non-negative value. Second, considering the factorization of non-negative similarity matrices, the resulting loadings will we or can be turned into positive Kiers (1997). Third, having nonnegative loadings we can consider a scaling to interpret the loadings as probabilities indicating the *representativeness* values that show how much an entity contributes to the clusters. Further mathematical details (including the optimization process) and implementational details of DESICOM can be found in Bauckhage et al. (2014); Kiers (1997). In the following section we present a use case of DESICOM for comparative spatio-temporal player profiling.

### 1.8.3 Case Study: Spatio-temporal Profiling of Player Traces in FPS Games

In this section we show how DEDICOM based models can be used for profiling players based on how they have moved around the game map. The presented case-study is part of the comparative analysis of player trajectories of famous first person shooter games that appeared in Bauckhage et al. (2014). The authors compared the behavior of DEDICOM and DESICOM to well known clustering methods in terms of trajectory based profiling. The main aim of is study is to provide insights to the designers about different kinds of behavior-based partitionings of maps. As a first step the authors consider encoding the spatio-temporal interactions on the game map through *waypoint-map* generation in which the spatial data is divided into Voronoi cells. After that a *waypoint transition matrix* is generated such that it captures the movements between the waypoints by assigning every positional point of a player to its closest waypoint and counting the transitions between the waypoints afterwards. Namely, an arbitrary entry of the waypoint transition matrix  $S_{ij}$  encodes the interactions between waypoint  $i$  and waypoint  $j$ . It is important to note the asymmetry of such a matrix, as players might be able to move from one particular sector of the game map to another while the opposite is not physically possible Bauckhage et al. (2014). Teleportation in *Quake III*

or falling down of the pit on Unreal Tournament’s DM-1on1-Serpentine can be given as examples of such a type of the spatio-temporal asymmetry in the movements of the players. After the extraction of the waypoints and their transition matrices, Bauckhage et al. (2014) compared the behavior of k-means, spectral clustering, DEDICOM and DESICOM for partitioning of the players traces of maps of *Quake III* and Unreal Tournament. While k-means performed poorly in capturing reasonable structures owing to the variance minimization nature of the algorithm, spectral clustering captured the spatial partitioning of the player behavior without the temporal information. On the other hand DEDICOM and DESICOM captured not only the spatial partitioning, which can be read off from the columns of  $\mathbf{A}$ , but also temporal directions among the partitioning, which can be directly read off from the values of  $\mathbf{R}$ . As a use cases for a comparative player trajectory analysis using DEDICOM family, we now present the insights from Bauckhage et al. (2014) where we analyze the results of DESICOM for two players (the complete analysis with three players can be found in Bauckhage et al. (2014)). Having extracted 250 common waypoints from the analyzed *Quake III* players played on the well known map *q3dm17*, Bauckhage et al. (2014) ran DESICOM with the same number of components over each of the player traces and analyzed the spatio-temporal profiles. We show the profiles of two of the players in Fig. 1.5. Based on the nonnegative and sparse loadings in  $\mathbf{A}$  the authors could identify the belongingness of the sector to it’s particular cluster and through  $\mathbf{R}$ .

Fig. 1.5a shows a *camper* player behavior that interacted mostly in a certain area of the map without moving around. DESICOM highlights this type of behavior by providing high amount of affinity from the yellow sector to the green sector (but not vise-versa). It is also important to note that, comparing the rows of the affinity matrix of this player, the high self-affinities are indicating that this player has not moved around but within the found sectors. Unlike the first player, Fig. 1.5b shows a *mover* type player that explored the map more intensively. Through the yellow, red and blue sectors, DESICOM, identified the player’s most frequently visited areas. Moreover, compared to the other types of players (explained in Bauckhage et al. (2014)), the higher affinity values between the sectors conclude that the player has not specifically moved around the found sectors showing no particular pattern. Through intelligent trajectory analysis such as DEDICOM and DESICOM, the highly complex player interactions can be compressed into more interpretable sectors and affinities between sectors. Methods like these are of obvious

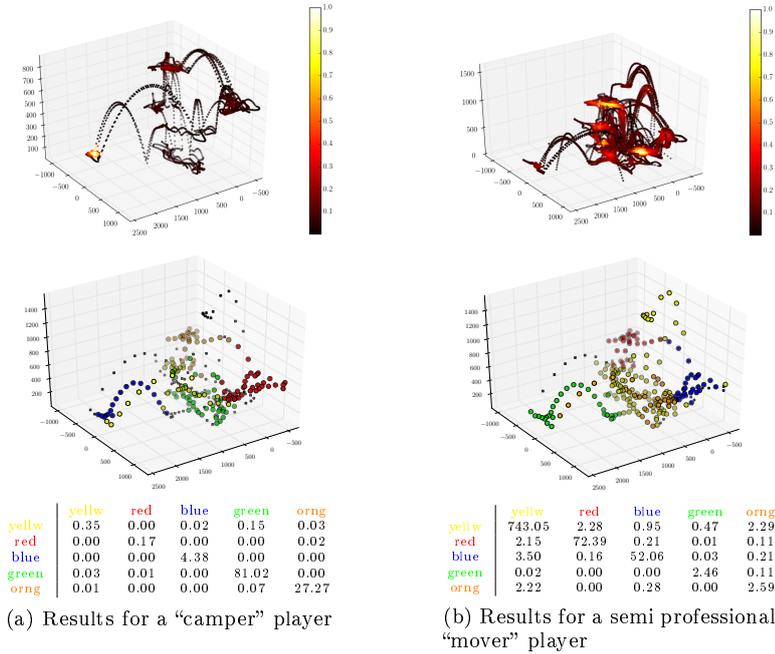


Figure 1.5 Comparative analysis (from Bauckhage et al. (2014)) of movements of two different players on the *Quake III* map *q3dm17*. From top to down each sub-figure respectively illustrates firstly a heatmap indicating the frequently visited areas on the map, secondly waypoints (in black) and found DESICOM (shown in color) and thirdly the found affinities between the found sectors. For details see Bauckhage et al. (2014).

interest to game designers and analysts that seek more insights about the players’ physical interactions in virtual worlds.

## 1.9 Discussion and Future Work

With the broad availability of detailed behavioral telemetry data in the game industry, and the increasing focus on freemium business models, there is a direct interest in techniques that permit evaluating player behavior in digital games. Behavioral profiling is one approach towards managing the common high-complexity, high volume, veracious and volatile telemetry data that characterizes game development. Profiling provides for a condensation and modeling of potentially complex behavioral spaces,

and permits the consideration of users in a quantifiable fashion, towards building an understanding about how people have played, how they are playing, and how they will play a game.

As discussed in this chapter, the specific techniques used for profiling exercises varies from simple aggregate statistics to machine learning. Each approach has its strengths and weaknesses and provide different venues of insights into the underlying consumer behavior. Profiling is carried out for a variety of purposes, from informing game design, driving monetization decisions, study human behavior, drive adaptive systems, and so forth. Shared for all of these purposes is that they attempt to provide data-driven insights to the relevant stakeholders, irrespective of whether they are from industry or academia. Game analytics is a domain which, at the time of writing and presumably in the near future, is in a state of rapid development due in part to the relative recent introduction of big data scale telemetry data, and in part due to the fast pace of innovation in games, as exemplified by recent years drive towards virtual reality and augmented reality games. For these reasons, it is difficult to use the current state-of-the-art to generate predictions of the future evolution of the field. However, there are specific gaps in the current knowledge which require future work, and which can pave the way for not only insights useful to the game industry, but also to the study of human behavior in online environments. These could be characterized as flagship areas in game analytics, and behavioral profiling has a role to play in all of them. These include but are not limited to the following:

1. **Cross-games profiling:** Given the high costs associated with acquiring players to a game - the User Acquisition Cost (UAC), there is a general interest in discovering techniques for migrating players between games in a company's portfolio. Doing so requires the ability to predict when someone will stop playing a particular game, and consumer profiles which can drive personalized advertising in order to try to convince a player to try out another game in the portfolio, rather than moving a competitor's game. I.e. profiles which inform what types of advertising strategies to leverage to drive players of a particular type to migrate Sifa et al. (2015c); Runge et al. (2014).
2. **Deep profiling in retention and monetization:** In most cases today the goal of predictive analytics is to drive a binary classification of players, e.g. into buyers and non-buyers, churners and non-churners. However, there appears to be an increasing interest in a broader classification which includes more detail, i.e. a more nuanced basis to make

decisions on. Furthermore, given the variety in the motivations for playing games, the variety of experiences games can provide and the varied personalities of consumers, deep profiling provides a toolbox for integrating varied player behaviors and experiment on potential correlations with player psychology.

3. **Modeling human behavior in online environments:** Unlike virtually any other online application, games can provide high-frequency and longitudinal telemetry data about human behavior in online environments. Some games are interacted with by players over several years. These data provide an unique opportunity to study human behavior. Not just in terms of direct observation, as exemplified by Sifa et al. (2014b) who observed regular patterns in playtime across more than 3000 game titles, or Feng et al. (2007) as well as Pittman and Gauthier-Dickey Pittman and GauthierDickey (2010), who investigated long-term behavioral patterns in a MMOG; but also from an experimental angle, i.e. trying to manipulate online environments to study how people react. There is a decades-long tradition for this kind of work in games research, for example in behavioral economics (see e.g. Knowles et al. (2015)).
4. **Adaptive games:** Adaptive games have been a topic of investigation in game AI for over a decade (e.g. Yannakakis (2012); Yannakakis and Togelius (2015); Yannakakis and Hallam (2009)). With the introduction of detailed telemetry streams, real-time adaptation has become possible and has already been integrated in some commercial games, e.g. the *Left 4 Dead*-series. Adaptation thus has a certain history in major commercial retail-based titles, but has also recently become a topic of interest in F2P games, across casual, midcore and hardcore genres. The interest relates to the potential for improving retention, user experience and monetization in games via real-time adaptation to individual or groups of players. Dynamic and predictive profiling here comes into play by providing the information required by adaptive systems.
5. **Cradle-to-Grave profiling:** As discussed in the beginning of this chapter, profiling can be driven by a variety of qualitative and quantitative data, across every phase of a product lifecycle. A practical challenge in this regard is ensuring the continuity of profiles across game productions, and the integration of different data sources. Drachen Drachen (2014) introduced the concept of cradle-to-grave profiling to describe this challenge, emphasizing that to accommodate the variations in data sources and technique availability throughout a product

lifecycle, player profiles would need to be iteratively updated in order to remain useful across changes in design, business goals, player behavior and the composition of the underlying user community.

In this chapter an overview and analysis of the state-of-the-art in player-focused, telemetry-based behavioral profiling has been presented, highlighting five main categories in contemporary work: snapshot, dynamic, predictive, spatio-temporal and psychological profiles. Each have their strengths and weaknesses and are applied to solve arrays of problems that inform decision-making processes. Focusing on telemetry-driven profiling, examples have been given for each of the four first categories. Within each category a broad range of statistical and machine-learning based methods can be utilized by professionals and researchers to evaluate player behavior. As the current work in behavioral profiling in games indicate, there is a substantial room for future work across industry and academia and every phase and aspect of the profiling process, for example algorithms, feature engineering, application and actionability of results, method evaluation and not the least communication of profiling results to stakeholders.

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