Introducing Archetypal Analysis for Player Classification in Games

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ABSTRACT

The analysis of user behavior in digital games has been aided by the introduction of user telemetry, which provides unprecedented access to quantitative data on user behavior from the installed game clients of the entire population of players. Behavior analysis is of interest to player experience testing because it provides evidence of problems affecting player experience. User telemetry datasets are generally exceptionally complex, featuring many variables recorded for a varying population of users over a temporal segment that can reach years. Classification of user behavior form a means for lowering the dimensionality discover behavioral patterns, providing behavioral profiles that are actionable to the UX-researcher or designer. There are numerous methods for unsupervised classification of user behavior, e.g. k-means/c-means, Non-negative Matrix Factorization, or Principal Component Analysis. Although all yield behavior categorizations, interpretation of the resulting categories can be difficult if not impossible. We believe this is a crucial aspect and therefore advocate the use of Archetypal Analysis which, in contrast, yields descriptive representations by embedding data into a space spanned by a few selected and unique behavior profiles. Extensive evaluation on a dataset containing recordings of 70,014 World of Warcraft ®players shows that Archetypal Analysis allows for a more accessible and easier data interpretation as all standard methods.

Categories and Subject Descriptors

D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*; K.8.0 [**General**]: GamesPersonal Computing; J.4 [**Computer Applications**]: Sociology, PsychologySocial and Behavioral Sciences

Keywords

Games, methodology, user experience, human-centered design, empirical methods (quantitative)

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1. INTRODUCTION

Contemporary digital games range from the very simple to the very complex, from the perspective of the potential range of user-game interaction options and the game mechanics integrated in these applications. For the AAA-level major commercial titles the tendency is towards increasing complexity, evident in game forms such as Massively Multiplayer Online Games (MMOGs) where hundreds of thousands of entities, objects and not the least players, form a tightly rules-governed but complex amalgam of potential or realized interactions [12, 2, 5]. The net effect of the trend towards increasing complexity paralleling technological development in digital games is to grant the user, or player, more ways of interacting with the game, which in turn leads to an increase in the space of potential player behaviors. This in turn leads to a challenge to user testing practices in the games industry as well as behavioral research, because the size of the behavioral space historically parallels the variety and complexity of player-game and player-player behaviors [19, 5].

Behavior analysis in digital games has recently been enabled for large sample sizes and substantial detail with the introduction of user telemetry data in game development contexts [19, 5, 12]. User telemetry is quantitative data about player-game or player-player interaction and is compiled in databases from logs provided from each game client. The user telemetry data are refined to produce game metrics, for example, combining telemetry data about total playtime and user IDs to obtain the game metric total playtime per user [12]. Any action the player takes while playing can potentially be recorded and stored. The approach forms a strong supplement to the practices of usability- and playability- testing, because user telemetry can provide the kind of detailed quantitative information on player behavior which is excessively time-consuming and in usually impossible to obtain using any other approach.

The analysis of player behavior via user telemetry is of interest to the investigation of User Experience (UX) in games (here Player Experience, PX), because it provides direct evidence of problems affecting the PX, for example indicating where in a game users have problems progressing or understanding the GUI [9, 5, 12]. Behavioral analysis can be carried out in numerous ways, and given the youngness of the approach in the context of digital games as compared with the over two decades of application in e.g. web analytics [10], behavioral analysis in games is likely in its infancy.

Player classification provides a means for analyzing complex game metrics datasets and distilling the results into behavioral profiles which can be acted upon to test and refine a game design (or specific parameters of a design) [1, 15]. In addition, behavioral classification provides the basis for selecting playtesting participants that cover the behavioral range of the users, which supplements traditional demographic approaches towards segmenting target audience for user-oriented testing [19, 9, 12]. Finally, classification of players based on their behavior forms a key line of investigation driving the research towards the development of adaptive games [25]. Unsupervised classification techniques vary, from simple clustering algorithms (e.g. k-means, c-means, Ward's Linkage) to the more complex (e.g. Non-negative Matrix Factorization (NMF) [14], Self-Organizing Networks (SOM)) [7, 1]. Different approaches have varied strengths and weaknesses, which can make it difficult for non-experts to decide upon a strategy for obtaining actionable insights into patterns of play.

In this paper, Archetypal Analysis (AA) [4] is introduced as a means for unsupervised behavior classification in game metrics datasets. Archetypal Analysis has has only recently been developed to a point where it can handle large-scale data [22], but carries the unique advantage over other classification methods that it does not look for commonalities between players, as is the case for e.g. clustering algorithms, but rather for archetypical players that do not reside within dense cluster regions. The individual player can then be described in terms of a combination of these archetypical players. This makes Archetypal Analysis inherently easier to interpret than other dimensionality reduction methods, which is crucial for most analysis tasks. We show the usefulness of AA by comparison to the traditionally used methods for classification of behavioral data (k-means, c-means and NMF, PCA). Evaluation is done on real game metrics data recored from the highly popular MMORPG World of Warcraft ®.

2. BACKGROUND AND RELATED WORK

One of the goals of behavior analysis in digital games is to inform Player Experience (PX) evaluations. The analysis of user behavior, whether through game metrics or analysis of screen capture video, provides a key link between PX and game design. For example, Microsoft Game User Research utilizes the TRUE system to link game metrics data with PX measures with substantial success [12], and this method has been adopted in other contexts within industry and research. Additionally, behavioral analysis can lead to the discovery of design problems affecting PX directly, e.g. sections of a game where the difficulty is too high, resulting in players breaching the frustration tolerance threshold [5].

It should be noted that the majority of previous work on game metrics analysis, and more specifically user behavior analysis, has focused on small sample sizes due to the lack of available large-scale datasets but also due to computational constraints. Additionally, research has (mainly) been focused on simple test-bed games, which are inherently simpler than AAA-level commercial games. Work on large-scale data in the context of commercial games is rarer, and highlights the need for robust algorithms to classify data which can scale to large datasets.

The fundamental approach in classifying user behavior is to reduce the dimensionality of a dataset, in order to find the most important variables, and express the underlying patterns in the user behavior as a function of these variables, e.g. via defining behavioral profiles which can be used to test/refine parameters of a game design [1, 15]. While it has only recently been adopted as a means of analyzing player behavior, the currently available literature is rapidly growing, notably within the domain of PX modeling or behavioral modeling for adaptive games e.g. [25]. Clustering algorithms have been explored as the basis for classifying player behavior, e.g. by [17], who used k-means clustering and support vector machines in predicting dynamic difficulty adjustments for a simple shooter-type digital game. [21] adopted frequency analysis to establish patterns of behavior among the player base of the MMOG *Cabal Online*, attempting to identify aberrant behavior which could indicate whether a specific character in the game was controlled by a program (a "bot"), usually developed to mine in-game resources (e.g. gold farming), or a human player. [6] utilized action frequencies in the MMOG *Star Wars Galaxies* to group player behaviors, focusing on a small set of player-player interaction behaviors. While these works were based on large datasets compared to traditional laboratory-based investigations, and commercial game titles, the methods adopted were relatively simple statistical models.

In comparison, [24] utilized a series of classification algorithms for recognizing player strategy in over 5000 replays of *StarCraft*, employing regression algorithms in order to predict when specific unit or building types would be produced. Similarly, [3], showed how large-scale variants of Archetypal Analysis could be used to analyze the evolution of *World of Warcraft* guilds. [5] employed Geographical Information Systems to provide analyses of spatial behavior for the game *Tomb Raider: Underworld*, showing how such analyses can assist game design. Furthermore, based on a selection of metrics from key game mechanics, [1] classified the behavior of 1365 players of *Tomb Raider: Underworld*, using Self-Organizing Networks and k-means clustering, locating four classes of user behavior that encompassed over 90 percent of the users in the dataset. These were translated into design terminology for use by the game's developers, Crystal Dynamics. In a follow-up paper, [15] classified a sample of 10,000 players using 8 categories of game metrics across more than 70 sub-sections of the game. The authors also demonstrated how behavior can be predicted based on analysis of early play profiles, which notably has relevance to persistent games such as MMOGs where users play the same game over periods potentially reaching years in duration. Similarly focused on prediction, [20] studied revisitations in online games focusing on either revisitation to a game or a game area, working with online access logs from 50,000 characters from the MMOG *Shen Zhou Online*, and 60,000 characters from *World of Warcraft*. The results indicated that it is possible to predict revisitations and patterns in these based on behavioral data from digital games.

The majority of current work on player behavior is with few exceptions based on simple test-bed games, or game metrics data from MMOGs. In comparison, the game industry has adopted the application of game metrics-based behavior analysis for online "social games", which includes MMOGs, but is mainly focused on games for social network platforms such as *Facebook* or *MySpace* [13]. In games of a persistent nature where the revenue funnel is based on subscriptions or micro-transactions, it is vital to be able to monitor the dynamics, behaviors and PX of a player- (user-) community, and this has generated an openness to data-driven design decisions which is an idea that has only in the past 2-3 years seen more widespread dissemination in the game industry, with developers still employing metrics-based analysis (and indeed game user research/game testing) in an informal capacity [16, 5].

The methods adopted for investigating player behavior are varied, from simple statistics to neural network-based modeling in the field of adaptive games. The approaches have different strengths and weaknesses, but there is a lack of comparative analyses, which forms the main motivation for the detailed experiments presented here. Furthermore, there is a general lack of research in data interpretability, which is notably important in a practical development context, where the results of a classification analysis should be as easy as possible to interpret. Considering the potentially massive size and increasing complexity of game metrics datasets, this is an important knowledge gap [23].

3. DATA AND METHOD

In the following, we introduce and discuss the game metrics dataset, obtained from *World of Warcraft*, and the classification methods selected for evaluation and comparison. Specifically, we compare k-means, c-means, NMF, PCA and AA, with an emphasis on the latter as it is here introduced in the context of games for the first time. It was found that c-means clustering results were functionally similar to k-means, so only k-means results are included here. A key assumption for all of the evaluated methods is that the game metrics data can be stored in a $d \times n$ matrix $\boldsymbol{V} = [\boldsymbol{v_1}, \dots, \boldsymbol{v_n}] \in \mathbb{R}^{d \times n}$, s.t. each column corresponds to a particular player or entity. The dataset being used consists of logs of the online playtime and leveling speeds from 70,014 players of *World of Warcraft*, recorded during a period of 2005-2010, i.e. several years of play. Please note that the dataset is not a complete recording of the players and that we had to fill/interpolate missing values. Data were obtained from mining the *Warcraft Realms* site. Only two behavioral variables were included here in the interest of clarity in comparing the ability of different methods to provide results translateable into actual player behavior.

3.1 Behavior Analysis by Clustering

Clustering is arguably one of the most common steps in unsupervised behavior analysis. Dealing with n samples of d-dimensional vectorial data gathered in a data matrix $\boldsymbol{V}^{d \times n}$, the problem of determining useful clusters corresponds to finding a set of $k \ll n$ centroid vectors $\boldsymbol{W}^{d \times k}$. If we express the membership of data points in $\boldsymbol{V}$ to the centroids in $\boldsymbol{W}$ using a coefficient matrix $\boldsymbol{H}^{k \times n}$, we note that clustering can be cast as a matrix factorization problem which aims at minimizing the expected Frobenius norm $\|\boldsymbol{V} - \boldsymbol{W}\boldsymbol{H}\|$.

Common approaches to achieve such a factorization include principal component analysis (PCA) [11, 8], k-means clustering (k-means), or non-negative Matrix Factorization (NMF) [18, 14]. It is important to note that while all these methods try to minimize the same criterion, they impose different constraints and thus yield different matrix factors. For example, PCA constrains $\boldsymbol{W}$ to be composed of orthonormal vectors and produces a dense $\boldsymbol{H}$, k-means clustering constrains $\boldsymbol{H}$ to unary vectors, and NMF assumes $\boldsymbol{V}$, $\boldsymbol{W}$, and $\boldsymbol{H}$ to be non-negative matrices and often leads to sparse representations of the data.

Another, less popular constraint expresses data as convex combinations of certain points in $\boldsymbol{V}$. The underlying problem can be formulated as $\boldsymbol{V} \approx \boldsymbol{V}\boldsymbol{G}\boldsymbol{H}$ where $\boldsymbol{G} \in \mathbb{R}^{n \times k}, \boldsymbol{H} \in \mathbb{R}^{k \times n}$ are coefficient matrices such that $\boldsymbol{H}$ is restricted to convexity and $\boldsymbol{G}$ is restricted to unary column vectors $\boldsymbol{1}^T \boldsymbol{h}_j = 1,\ \boldsymbol{h}_j \succeq \boldsymbol{0}$, and $\boldsymbol{g}_i = [0, \dots, 0, 1, 0, \dots, 0]^T$. In other words, the factorization approximates $\boldsymbol{V}$ using convex combinations where the basis vectors $\boldsymbol{W} = \boldsymbol{V}\boldsymbol{G}$ are data points selected from $\boldsymbol{V}$. The goal now is to determine a basis that minimizes the Frobenius norm $E = \left\|\boldsymbol{V} - \boldsymbol{V}\boldsymbol{G}\boldsymbol{H}\right\|^2 = \left\|\boldsymbol{V} - \boldsymbol{W}\boldsymbol{H}\right\|^2$.

When minimizing the Frobenius norm, we have to simultaneously optimize $\boldsymbol{W}$ and $\boldsymbol{H}$ which is generally considered a difficult problem and known to suffer from many local minima. Archetypal Analysis (AA) as introduced in [4] applies an alternating least squares procedure where each iteration requires the solution of several constrained quadratic optimization problems. It solves the case where $\boldsymbol{G}$ is restricted to convexity instead of to unarity. Until recently, Archetypal Analysis was restricted to smaller datasets; however, recent work has discovered ways of extending Archetypal Analysis to large-scale datasets, making the method effective for implementation in the context of game metrics[22].

3.2 Interpretable Cluster Centroids

The goal of unsupervised behavior analysis is an interpretable representation of the data as the representation basically has to assist a human in analyzing huge amounts of game metric data. Ideally, one could assign a simple expressive label to each found basis vector or centroid. While there is no objective criterion on what a descriptive representation is, it is widely assumed that approaches yield interpretable results when they embed the data in lower dimensional spaces whose basis vectors $\boldsymbol{W}$ correspond to actual data points. This is the case for AA as the archetypes the method produces are restricted to being sparse mixtures of individual data points, which therefore are interpretable by non-experts, which makes the method interesting as a means for player classification because it does not require expert knowledge to interpret the results. This contrasts with other dimensionality reduction methods such as PCA [11] where the resulting elements can lack physical meaning; and NMF which yields characteristic parts, rather than archetypal composites [7]. k-means clustering is similar to AA as the basis vectors reside within cluster regions of the data samples, however, the centroids do not necessarily have to reside on existing data samples.

Besides simply considering existing data samples, it showed to be useful to search for certain extremal elements in a set of data and to represent the data by means of convex combinations of these extreme points as it is done for AA. Searching for extremal points accommodates human cognition, since memorable insights and experiences typically occur in form of extremes rather than as averages. Philosophers and Psychologists have noted this for long, since explanations of the world in terms of archetypes date back to Plato. According to C.G. Jung, it is the opposition that creates imagination. Every wish immediately suggests its opposite and in order to have a concept of good, there must be a concept of bad, just as there cannot be an idea of up without a concept of down. This principle of opposites is best summarized by Hegel's statement that "everything carries with it its own negation". The only way we can know anything is by contrast with an opposite. By focusing on extreme opposites,

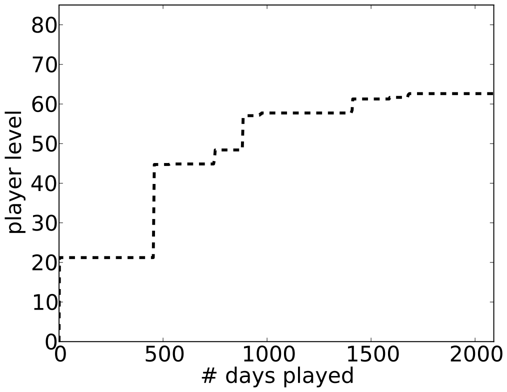


Figure 1: Level/time plot of a specific player. The x-axis is shows a timeline, the y-axis indicates the current level of the player.

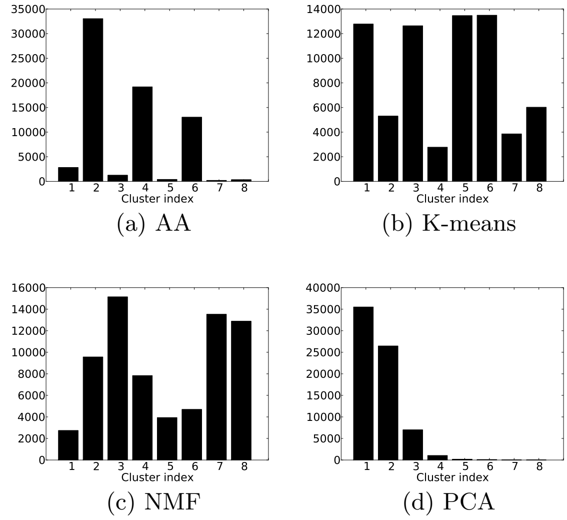


Figure 2: Hard assignment of data samples to cluster centroids for AA, k-means, NMF, and PCA.

we simply enlarge the margin of what we know and in turn our chance to separate things. In contrast, k-means clustering focuses on the average and is therefore in the context of other centroids usually more difficult to interpret. While the centroid vectors all cover different regions of the data space, their overall similarity is often too high as it would help a human observer in assigning it a concrete label.

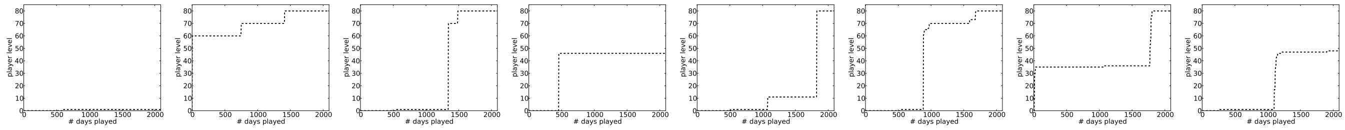
4. RESULTS

Our intention here is to investigate how common clustering techniques perform on game metric data with respect to (**a**) descriptive representations, (**b**) cluster separation. The World of Warcraft ®dataset contains for a set of players recordings of their online time and their level for a specific date. We aggregate the recordings into a 2.555 dimensional feature vector where each entry corresponds to the level the player reached for each day in the last 6 years. A typical feature vector can be seen in Figure 1. Note that the maximal level of a character was increased twice via expansion packs (from levels 60 to 70 and 70 to 80) during the period of recording (and in December 7th 2010 a third time, following the end of the data logging period, from levels 80 to 85), usually when a new expansion got released (evident as stepwise increases in several of the profiles in Figure 1).

We applied AA, NMF, k-means, c-means and PCA to the dataset. Note that unsupervised methods usually suffer from the problem of having no objective way of defining threshold values, which makes the definition of the number of classes to use a subjective decision. These aspects of classification analysis add to the difficulty in adopting these methods by non-experts in a game design/development context. For the presented experiments we set the number of basis vectors/classes to $k = 8$ based on a consideration of variance explained vs. retaining a useful number of basis vectors with respect to the end goal being to produce player classes that are significantly different behaviorally.

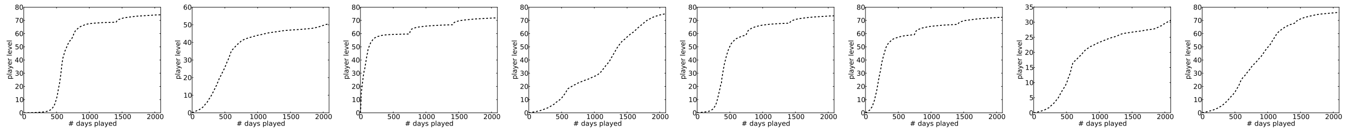
The resulting basis vectors or cluster centroids are visualized in Figure 3, Figure 4, Figure 5, Figure 6. For example, Figure 3(a) shows the level/time history plot of a specific player who only very slowly increased his experience level from level 10 to level 20, and Figure 3(b) shows a player who quickly increased his level to 70, and then after some time to level 80. These two player types can be immediately labeled as "casual player" and "hardcore player". Comparing the resulting basis vectors of the different methods shows that, as expected, only for k-means clustering an AA we obtained an interpretable factorization. However, the k-means centroids (Figure 4) are overall very similar and do not allow a straight forward labeling. Basically, they all show the same curve and only their slope varies slightly. In contrast, the AA basis vectors in Figure 3 are intuitively easier to interpret. From these, we can also make assumptions about the leveling behavior of the players as the steepest increase in the level seems to correlate with the release of expansion packs and the simultaneous increase of the maximal level. The basis vectors of PCA and NMF are, as expected, not or only partly interpretable.

Besides a descriptive representation a quantitative discrimination of player types is desirable - i.e. how many players that belong to each behavioral class. This, however, is only fully supported for k-means clustering as it is the only method that builds on hard cluster assignments, with each sample belonging to only one particular cluster. The other methods are usually soft (or more precisely linear, convex, or non-negative) combinations of their basis vectors. This means that players are expressed in terms of their relationship to each of the eight behavioral profiles (basis vectors) located, and summarily grouped (clustered) according to their distribution in the space spanned by the basis vectors. For the numbers of players belonging to each basis vector provided here (Figure 2), players have been assigned to the nearest basis vector (behavioral profile). This provides clear profile divisions, however, a more precise way of grouping players would be to define clusters in the space extended by the eight basis vectors. The results indicate that the distribution of players to eight basis vectors across the four methods included (Figure 2) are not similar, with AA and PCA indicating three large groups, and k-means and NMF a division into four large and four smaller groups each.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 3: Basis vectors for Archetypal Analysis reside on actual data samples (players in this case) and are therefore easier to interpret. The selected players or archetypes are often polar opposites which further supports interpretability.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 4: Cluster centroids for k-means clustering reside on center locations of cluster regions. While they accurately represent a broad number of players, they are overall very similar to each other and do not allow straight forward interpretation.

5. CONCLUSIONS AND DISCUSSION

In the above four different commonly used methods for clustering data derived from humans and human behavior (k-means, c-means, NMF, PCA) have been applied with the purpose of defining classes of player behavior based on a game metrics dataset from the MMOG *World of Warcraft* using two behavioral variables: playtime and leveling time. The effectiveness of these methods, previously employed to analyze game metrics datasets, have been compared with Archetypal Analysis (AA), which has only recently been adopted for use with large-scale datasets and not previously employed in behavioral classification of game players.

The results indicate that different approaches towards classifying player behavior in digital games have different strengths and weaknesses. K-means/c-means clustering allocate players directly to groups, via cluster centroids, that are defined by specific behaviors, whereas NMF, PCA and AA initially provide basis vectors which span a space that players fall within, which means that players can be described in terms of their relationship with each basis vector ("behavior type") and grouped (clustered) according to their distribution in the space spanned by the basis vectors. While this might appear to make clustering more attractive than the other methods as it saves a step in the analysis, there is an important drawback: the clusters tend towards being similar and thus not conducive to interpretation in terms of differences in the behavior of the different clusters of players.

A similar interpretative problem is evident for NMF and PCA, which provide results that are counterintuitive to the underlying behaviors. For example, players can be seen to loose levels, something that is not possible in *World of Warcraft* (Figure 5, Figure 6). While NMF and PCA may provide valid basis vectors from a methodological perspective, based on the available behavioral data, these are not intuitively interpretable in terms of the behavior of the players. In comparison, AA and k-means/c-means (Figure 3, Figure 4) provide basis vectors that are intuitively interpretable from the perspective of the underlying behaviors they signify. Only AA, however, has in the presented case resulted in basis vectors (archetypical behaviors) that are significantly different, and thus meaningful in a behavioral analysis. The results presented thus indicate that AA is a potentially useful method for the classification of player behavior in games, presenting intuitively interpretable behavioral profiles.

On a final note, the results presented indicate that the choice of method plays a substantial role in defining the result of large-scale game metrics analysis, and highlights the challenges faced by the game industry and -research environments looking to evaluate user behavior at the scale that has become possible with the introduction of game metrics logging in game development. There is a clear need for research addressing issues such as scaling effects, data types and methodologies for analysis. This is in addition to the overall question of how to relate user behavior to user experience measures. We should note that this is ongoing research and that we will focus in the future on employing AA to the analysis of game metrics datasets from other games than *World of Warcraft*, increase the diversity of features and explore, e.g. if emerging player classes change during the duration of a game with a finite start and end.

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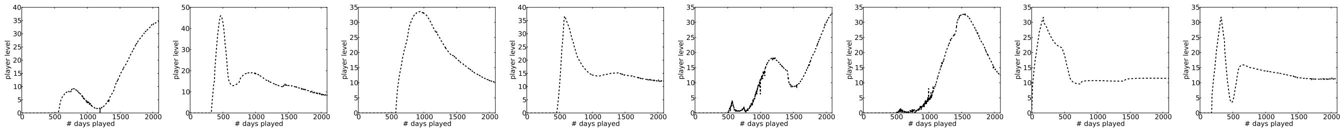
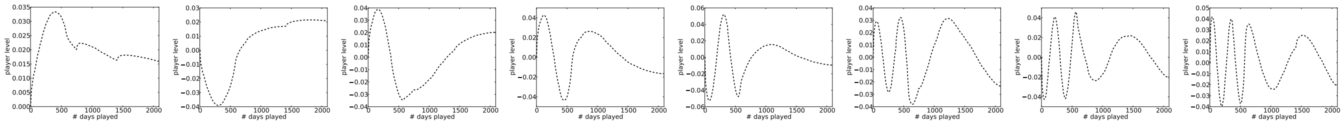


(a) (b) (c) (d) (e) (f) (g) (h)

Figure 5: Basis vectors for non-negative matrix factorization represent parts of original data samples. As they are stricly positive, they allow for interpretation but they do not correspond to actually existing players.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 6: Basis vectors for principal component analysis do not correspond to actual players and are also not interpretable.

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