

Modeling Player Preferences in Avatar Customization Using Social Network Data

A Case-Study Using Virtual Items in Team Fortress 2

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Abstract—Game players express their values related to self-expression through various means such as avatar customization, gameplay styles, and interactions with other players. Multiplayer online games, now often integrated with social networks, provide social contexts in which player-to-player interactions take place, for example, through the trading of virtual items between players. Building upon a theoretical framework based in computer science and cognitive science, we present results from a novel approach to modeling and analyzing player values in terms of both preferences made in avatar customization, and patterns in social networking use. Our approach resulted in the development of the Steam-Player-Preference Analyzer (*Steam-PPA*) system, which (1) performs advanced data collection on publicly available social networking profile information and (2) the AIR Toolkit Status Performance Classifier (*AIR-SPC*), which uses machine learning techniques including clustering, natural language processing, and support vector machines (SVM) to perform inference on the data. As an initial case-study, we apply both systems to the popular, and commercially successful, multi-player first-person-shooter game Team Fortress 2 by analyzing information from player accounts on the social network *Steam*, together with avatar customization information generated by the player within the game. Our model uses social networking information to predict the likelihood of players customizing their profile in several ways associated with the monetary values of the players’ avatar.

I. INTRODUCTION

Multi-player online games have become more prevalent in recent years, just as have social networking sites such as Facebook and Twitter. The integration of social networks with videogames has allowed players/users to utilize knowledge from one domain within the other in order to improve user experience and engagement. For example, in a multi-player game, players can rely on the social network’s list of friends to find other players to play with. In most of these games, players take control of a virtual avatar that resides in the virtual world. These avatars are often customizable in order to allow players to personalize them to their liking, often as a way of expressing one’s identity.

In this paper, we present results from analyzing both the social networks of players on the distribution platform *Steam*, and categories revealed by preferences players exhibited by customizing their avatars in the multi-player first person shooter Team Fortress 2 (TF2), both of which are developed and maintained by Valve Inc. First we use our system, the Steam-Player-Preference Analyzer (*Steam-PPA*), to collect and aggregate publicly available data from *Steam*, TF2, and additional community websites. Then, using our system called

the AIR Toolkit Status Performance Classifier (*AIR-SPC*), we identify and categorize a dataset of players. This categorization is based on what we have termed their **status performance**, the monetary value of their customized avatar within the game. We highlight a correlation between a player’s social network usage and the exhibited status performance. Finally, using artificial intelligence (AI) machine learning techniques, we showcase the effectiveness of Support Vector Machines (SVM) in predicting and classifying a player’s status performance using only the information from the social network, such as the presence or absence of strong social connections to other players, which we term **social status**. The upshot is the we were able to classify players in our test set of 152 user profiles in this manner with a surprising degree of precision (69%).

This paper presents the following contributions to research in computational intelligence. First, the development of the *Steam-PPA* system which enables collecting publicly available data from players from the *Steam* network (using the official API) as well as the *Steam* Community (by parsing publicly available community pages) using a common interface. The *Steam-PPA* system has caching enabled to reduce unnecessary network queries.

Second, we introduce the notion of a player’s status performance in games by choices exhibited in avatar customization through the equipping and collecting of virtual items. We calculate community-derived real-world monetary values of these items, which form a quantitative measure of some aspects of player preference. We use the AI k-means clustering technique to identify clusters of players based on their status performance in an unsupervised manner, clustering the players into categories according to their preference (status performance).

Third, we extend work on predicting social connections called “tie strength” [1], [2] in social networks and apply it to the *Steam* network [3] as a new domain. *AIR-SPC* makes use of natural language processing (NLP) for sentence and word segmentation when collecting public user information (e.g., wall posts), and then performs sentiment analysis for classifying the words according to the emotions they convey.

Fourth, we demonstrate the effectiveness of dimensionality reduction (from ten variables to four) using Principal Component Analysis (PCA) over a dataset of player profiles, aggregated using the *AIR-SPC* system, to create a smaller set of features which still sufficiently describes the whole, original dataset. We analyze the resulting principal components

to obtain more abstract and human understandable ways to reason about the distribution of the players based on their social network, which we shall refer to as their **social status**.

Fifth, combining the results from calculating status performance and the social statuses of players, we exhibit a correlation between the two relatively separate domains of the social network and the game. Finally, we highlight the ability to use AI learning and classification techniques (Support Vector Machines) to predict a player’s gameplay preference (status performance) using the player’s social networking information (social status).

The rest of this paper is structured as follows: Section II provides background information on the application domain of *Steam* and TF2. It describes the class of virtual items called **hats** within the game, which is the focus of our current status performance experiments. Section III covers related work in social network tie strength estimation, player modeling and clustering using telemetry data. Section IV describes the system design and framework of the implemented system. It also details the methods we employed, covering data collection, experiments performed, and techniques used to interpret and analyze the data. Section V presents the results and analyses of our experiments. Section VI is a discussion of the implications of our research. We conclude with a summary in Section VII, and discuss about potential future work and the applicability of our approaches to other applications in Section VIII.

II. APPLICATION DOMAIN

A. *Steam*

*Steam*¹ is an integrated game distribution platform and social networking site (along with some additional functionality). *Steam* allows users to manage their collections of games purchased using it. *Steam* requires users to sign up for a *Steam* account with a unique *Steam* Id in order to create individual *Steam* Profiles. The games available include both first-party (published by Valve) and third-party titles. In terms of social networking, players using *Steam* connect to one another through their friends lists, which can be used to send messages, view others’ profiles, or find others to play with. Players may also create, manage and join “groups,” which are communities of players with similar interests. *Steam* also allowed users to connect to other social networking applications, such as Facebook. In 2011, there were approximately 82.2 million friendship edges, 1824 games and 1.98 million groups [3]. The number of player’s concurrently active on *Steam* is between 2-4 million, at the time of writing. The size of the network, along with its gamer-centric demographic, makes it an interesting domain in which to research the relationships between social network behavior and player gameplay.

B. *Team Fortress 2*

The online multiplayer first-person-shooter (FPS) videogame *Team Fortress 2*² (TF2) was released in 2007. There are nine character classes, each with a unique visual 3-dimensional (3D) model, attributes, abilities, and weapons. though they may create multiple characters and switch classes.

Each team is often composed of players playing as different classes, as each class has strength and weaknesses which teams need to balance out in order to be more effective at accomplishing their goals.

C. *Virtual Hat Items*

The focus of this paper is on analyzing one particular category of virtual items in TF2, which are the items equipped on a player’s head, called **hats**. They have become one of the most popular virtual items for players in TF2, which has prompted Valve to promote TF2 as “America’s #1 war-themed hat simulator”. The hats are obtained through various means, with the most common being purchasing using real-world currency³. Some of the hats are released as promotional items in tandem with game releases on *Steam*. Most are limited in supply, which becomes quite apparent to players once promotions end. Hats differ from most virtual items used in various other multiplayer online games in that they often provide no functional benefits to the player wearing them. Yet, despite this, it was estimated to be worth around \$50 million US in 2011 [4], with transactions, negotiations and trades occurring on both *Steam* and third-party community sites, prompting Valve to hire an economist to manage their in-game economies⁴. The equipping of avatars with these hats thus forms an interesting case of self-expression, since the decision to equip (wear) a particular hat for a particular character class does not improve player attributes or states within the game in order to gain an advantage. Instead diverse hats seem to be equipped based upon issues such as scarcity, style, personal taste, and other subjective factors. The diversity in the type of hats are a result of their method of acquisition/distribution, their capabilities of being customized (i.e., by color), and their rarity. A particular class of hats, with less than 1% chance of being “uncrated” and with special attached particle effects, are termed *unusuals* and are particularly valuable, with a single Unusual able to fetch up to around \$2000 US on its own. This poses the question of whether any of this data describing the diversity of hats worn could be used to better explain or predict player hat acquisition, collection, and use.

III. RELATED WORK

This paper draws upon several research areas including sociology, cognitive science, and game studies, along with artificial intelligence and machine learning techniques for clustering, natural language processing, supervised learning and classification. A brief account of important references are outlined as follows.

Game studies scholar Christopher Moore provided, to the best of our knowledge, the first scholarly account of the various aspects of TF2 such as virtual items and achievements, and their implications for players’ real-world identities [5]. We share Moore’s motivation for studying **hats** in TF2 as artifacts expressing players’ preferences, arguing that they form “achievements, but not representation of skills,” and that “meaning is routed through the absurd-ist quality of the games’ melange of historical, philosophical and popular

¹Official Website: <http://store.steampowered.com/>

²The latest version, as of writing, is v1.2.6.1, released on 27 March 2013

³In practice players actually purchase *keys* to unlock randomly dropped Crates in the game in which hats may be found.

⁴Valve Economics: <http://blogs.valvesoftware.com/economics/>

pastiche, individual taste and expression.” AI researcher Hugo Liu has argued that social networking profiles often constitute taste statements, which can be used to define a user’s **taste performance** [6], and can be viewed as a computational instance of what sociologist Erving Goffman classically termed everyday self-presentation or performance [7]. We extend upon the notion of taste performance by considering the performance of avatars controlled by players, which can be viewed as what James Gee calls “projected identities” that incorporate elements of both real and the virtual identities [8].

Social scientist Nick Yee, et. al., [9] showcased how online player data could be used for discovering relationships between virtual behavior, and a player’s real-world personality profile. When real-world cultural ideas of the human player are projected onto the avatar, the result is a type of blended identity that computer scientist and digital media scholar D. Fox Harrell terms a “phantasmal identity” due to its blend of sensory imagery with concepts drawn from particular worldviews regarding social categories [10]. Harrell has argued that current computational identity systems are limited in their ability to adequately represent the “dynamic contingency of real life identity experiences” [11], and introduced the cognitively-grounded Advanced Identity Representation (AIR) model for developing identity representation technologies which overcome such limitations [12] by enabling dynamic, cross-domain user self-representations (e.g., between social networks and games). An outcome of research in the AIR Project is the continuing development of the AIR Software Toolkit, of which *AIR-SPC* is a part, to support more robust and dynamic forms of user/avatar categorization and users’ deployment of multiple self-representations for different purposes [13].

Computer scientists Roi Becker, et al., [3] have analyzed the *Steam* network and highlighted, among other results, that the “friendship ties,” or number of friends per user, correlated with activity on the network. Their definition of “ties” differs from ours. We use a more formal definition of measuring the relationship between people, based on several factors defining a player’s social network, termed **tie-strength** by sociologist Mark Granovetter [2]. He outlined the importance of considering weak ties for “discussion of relations between groups” and for analyzing “segments of social structure not easily defined in terms of primary groups”. Eric Gilbert and Karrie Karahalios have identified ways to predict tie strength in social media [14]. Ferrera et al., point out the roles of both strong and weak ties in the Facebook social network [?]. These illustrate that social networks are appropriate systems to analyze and understand features of a person’s real-world identity and social structures.

Machine learning clustering and classification algorithms in multiplayer games have been performed by AI researchers Anders Drachen, et al., who used k-means clustering and Simplex Volume Maximization (SiVM) on high-dimensionality telemetry data (e.g., playing time, kill/death ratio) to categorize players according to behaviors [15]. K-means clustering and Support Vector Machines (SVM) have been used for dynamic difficulty adjustments for shooter-type games [16] and for automatic preference modeling of virtual agents in strategy games [?], showing the effectiveness of AI clustering and classification for performing player inference in multiplayer online games.

IV. METHODS

A. Data Collection

We collected and analyzed approximately 200 profiles on the *Steam* network in order to calculate the predictive variable for measuring tie strength (to be described below). Calculating some predictive variables like mutual friends had the effect of exponentially increasing the number of profiles required to be queried, resulting in tens of thousands of player summaries, item listings, wall comments and application listings that had to be collected. Due to the privacy settings on some of the profiles which either restricted or blocked queries or requests, we filtered the number of profiles to 152 that contained sufficient data to be analyzed according to the predictive variables. These profiles were collected using our implemented *Steam Player-Preference Analyzer (Steam-PPA)* system described below⁵. It is composed of three main layers, and Fig. 1 depicts an overview of the system.

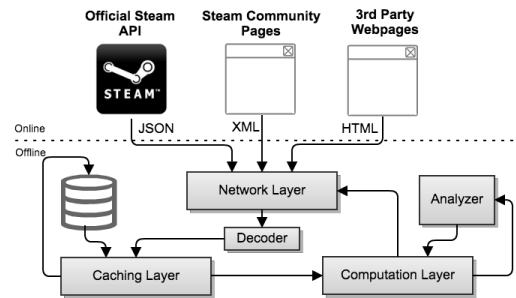


Fig. 1: Overview diagram of the implemented system.

The network layer directly makes requests to remote servers online in querying for game, social network or player information. The decoder is used to parse and extract appropriate information from the results of the queries. There are three main types of remote servers: 1) The Official *Steam* API, which requires an authentication key gives access to information about games on the *Steam* network (e.g., schema of all the items in TF2) and player profiles on the steam network (e.g., summary of player avatar name, player’s friends). Requests are limited to 100,000 API calls per day, and are returned in JSON format; 2) *Steam* Community Pages, HTML pages maintained and owned by Valve/Steam. They provide common social networking capabilities (e.g., wall posting, picture uploading, user-to-user messaging); 3) 3rd-Party Webpages, which are external sites unaffiliated with Valve/Steam. One site that was used as part of system is Backpack.tf⁶, a site which crowd-sources prices on all the items available in TF2. These kind of sites are referenced by players in order to negotiate and trade with one another, using the site’s price-listings in order to establish agreement on the real-world monetary value of items.

To keep within the *Steam* API limits and prevent unnecessary queries, we implemented a caching layer which stores all the decoded data received, via the decoder from the network layer, onto the hard disk. Timestamps are added to the cached

⁵We plan to release this system publicly in the future, and thus provide some technical details about its implementation and usage here.

⁶Website: <http://backpack.tf/>

data and stored as either JSON or XML files. The caching layer is also used to store intermediate results from the computation layer, such as the computed hash table containing prices for each item, for efficiency.

The computation layer interfaces with both the network and caching layers, and is responsible for computing results and results from the raw, cached data. For instance, in determining the number of common applications that a user shares with each of the user’s friends, it needs to get the friend list of the player (*Steam* API) and the lists of each players’ and their friends’ application list (from the *Steam* Community Page). Section IV outlines the more complex scenario of calculating the real-world monetary value of a player’s customized avatar using a combination of data sources, as well as how the computation layer calculates various sets of values based on metrics of tie strength.

B. Player Social Network Inference using Tie Strength

We referenced Gilbert, et al., and their work in predicting tie strength in social networks by collecting information on various aspects of a user’s social networking profile called predictive variables [14]. They showed that by using a combination of predictive variables such as a user’s number of friends, the number of words exchanged, or the length of time two users have known each other, the tie strength between the users can be estimated [1], [2]. We extend upon their work in applying it to our application domain of *Steam* and TF2. In *AIR-SPC*, we implemented the collection of ten predictive variables, spanning five of the seven types of predictive variables proposed by Gilbert, et al., [14]. The categories are described as follows, with the index of the predictive variable specified in parentheses before its name.

1) *Intensity Variables*: The number of (#1) Own Wall Posts, (#2) Friend Wall Posts and (#3) the number of Wall Words Exchanged are intensity variables. The *Steam-PPA* system collects all data for these variables by parsing the *Steam* community pages of each user. The parser isolates tags on the page corresponding to wall posts, and differentiates between posts made by the player or by the player’s friends by cross-referencing IDs against the friend list from the cached *Steam* API data. It then uses the Python Natural Language Toolkit (NLTK) library to perform sentence and word segmentation.

2) *Intimacy Variables*: Consists of the (#4) friend count, which is the size of the list of friends queried and returned from the *Steam* API. *Reciprocal Services Variables*: Consists of the (#5) traded items count, which is calculated by querying for a player’s entire set of virtual items, and counting those which were obtained by trading and (#6) average number of common applications. The *Steam-PPA* system obtains the list of applications by parsing the *Steam* community pages of a player and each friend profile in the list of friends.

3) *Emotional Support Variables*: Consists of the (#7) Positive Emotion Words and (#8) Negative Emotion Words. The *Steam-PPA* system uses NLTK for word and sentence segmentation and performs sentiment analysis using the Python `sentiment_classifier` package.

4) *Structural Variables*: Consists of the (#9) Average Mutual Friends and (#10) Average Common Groups of each

player. Both of these values are calculated in *Steam-PPA* by querying for the list of friends and list of groups using the *Steam* API.

C. Calculating Status Performance using Hat Customization

In order to quantify performance in avatar hat customization in TF2, we consider status performance consisting of a tuple of two values, the collected value, referring to the total monetary value of hats in a player’s inventory, and the used value, the total monetary value of hats actively equipped across all of the player’s characters in any of the classes in TF2.

Calculating the monetary value of a hat requires *Steam-PPA* to first use the *Steam* API to get a player’s list of all items. It then filters the items to only hats. It then parses a third-party price-listing website to get the prices for regular hats, as well as prices for *unusuals*. Fig. 2 shows the a flowchart of *Steam-PPA* performing the necessary queries in order to calculate the value of any hat a player possesses.

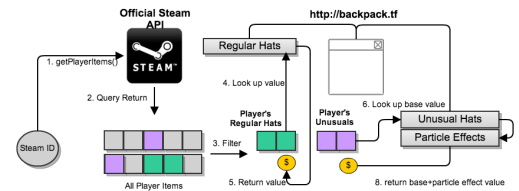


Fig. 2: A flowchart illustrating how *Steam-PPA* performs several look-ups to calculate the monetary value of hats.

D. Identifying Status Performance Categories with Clustering

To ameliorate the variation in calculated status performance across the dataset of players, we performed k-means clustering in order to identify groups of players with similar levels of status performance. We made use of the Bayesian Information Criterion (BIC) and the within-sum-of-squares error to help decide on the optimal number of clusters. This allows us to map each data status performance value onto a smaller set of categories through cluster classification, making it easier to describe the distribution of status performance across the dataset in terms of discrete labels.

E. Social Status via Dimensionality Reduction with PCA

We performed dimensionality reduction on the set of features using Principal Component Analysis (PCA). Given a dataset, performing PCA decomposes the data into several components, each defined as a linear combination of the original set of features using coefficients. Performing PCA on our dataset allows us to 1) reduce the number of features required to describe the dataset, and 2) infer relationships between the original features through the coefficients used in each principal component. Studying the resultant principal components and their coefficients allows us to reason about the data with more abstract, higher-level terms which we define as the social status of the player. This allows us to describe each player’s social network in **social status** (principal components) terms, instead of the original, fine-grained individual tie strength predictive variables.

F. Predicting Status Performance with Social Status

The first step we took in studying the relationship between social status and status performance was to analyze the degree of association of the discrete status performance labels with social status. We performed k-means clustering on the resulting social status from PCA, and then use coefficients of associations tests to study any relationship between both set of clusters. A stronger relationship we explored, is the hypothesis that a player’s social status can be used to predict status performance. The social status principal components are used as the set of features, while the status performance labels form the set classes to classify each player as. We make use Support Vector Machines (SVM) to first train on the data to create such a classification model. We may then use the trained SVM model to perform prediction of a player’s status performance based on an input feature set of status performance principal component values.

V. RESULTS & ANALYSIS

A. Predictive Variables

Table I contains a summary of each of the ten raw predictive variables of tie strength that were collected and processed across the dataset of the resultant 152 player profiles on the *Steam* network.

Dimension	Variable Name	Mean	Med.	Std. Dev	Min	Max
Intensity	Own Wall Posts	0.783	0.00	2.30	0	15
Intensity	Friend Wall Posts	7.428	1.00	12.92	0	50
Intensity	Words Exchanged	65.79	6.00	121.73	0	600
Intimacy	Friend Count	90.02	67.50	76.06	1	299
Reciprocal	Traded Item Count	10.39	0.00	29.19	0	214
Reciprocal	Common Apps.	14.096	9.55	14.15	1	95.97
Emotional	Positive Words	63.41	6.00	117.02	0	580
Emotional	Negative Words	2.382	0.00	5.41	0	34
Structural	Mutual Friends	5.986	4.10	5.71	0	31.24
Structural	Common Groups	1.016	0.791	0.890	0	3.77

TABLE I: Predictive Variable Summary of Collected Profiles.

B. Virtual Items: Equipped & Inventory Values

We projected each player’s status performance monetary value as a 2-dimensional point (*equipped*, *inventory*). Table II provides a numerical summary of the distribution of both types of values. Fig. 3 shows a scatterplot of the logarithmic plots of inventory value versus equipped value of the virtual hats across the player profiles.

	Mean	Median	Std. Dev	Min	Max
Equipped	\$32.57	\$2.10	\$119.89	\$0.00	\$1151.88
Inventory	\$18.34	\$1.40	\$84.82	\$0.00	\$867.87

TABLE II: Summary of the monetary value of hats for equipped and inventory.

Next, we performed clustering on the dataset to obtain discrete, nominal classes in order to perform classification. We can now more precisely use the term Status Performance for these classes. We performed k-means clustering, varying the cluster sizes between 1 and 15, and used the within-group sum of squares as a measure of an ideal number of clusters. This is plotted in Fig. 4.

Pairwise Comparison of Inventory Value vs. Equipped Value

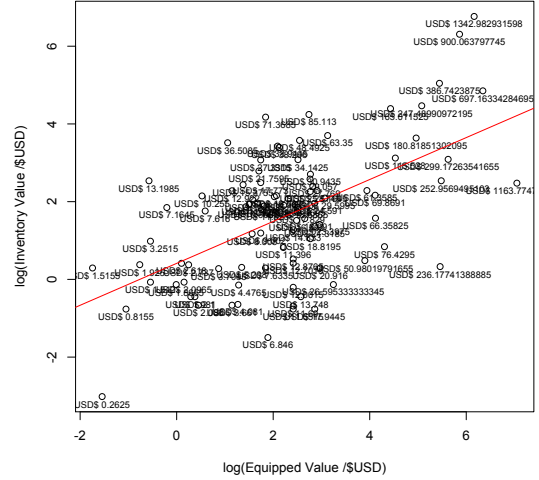


Fig. 3: Scatter plot of players using the log-values of inventory vs. equipped item. Each label is the sum of the inventory and equipped values. There exists a high and positive correlation between the two variables (Spearman’s $\rho = 0.67$, $p < 0.01$).

Variation of Errors with Varying Clusters Size

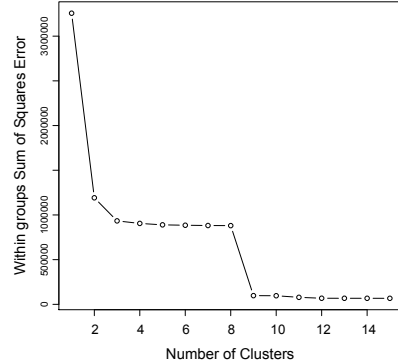


Fig. 4: Graph showing the within-group sum of squares error plotted against the number of clusters.

Fig 4 shows that a similar within-group sum-of-squares occurs for values between three to seven, with the highest change between k-value two to three. We ignore values of $k \geq 7$ as over-fitting seems to have occurred. We also used model selection according to the Bayesian Information Criterion (BIC) for Expectation-Maximization (EM). Thus, we chose $k = 3$ to be the ideal number of clusters (BIC= -1997). Next, we hand-assigned labels to each cluster, defining our status performance labels, the results of which are shown in Table III.

C. Principal Component Analysis on Predictive Variables

We performed PCA on the dataset of player profiles, each defined by the ten tie strength predictive variables, to reduce the dimensionality of variables to describe the dataset. Table IV shows the top four principal components obtained.

	Cluster 1	Cluster 2	Cluster 3
Equipped	\$0.24	\$8.65	\$193.13
Inventory	\$0.41	\$6.79	\$102.41
Frequency	65	23	64
Status Performance	LOW	MEDIUM	HIGH

TABLE III: Status performance clusters, and their mean points.

	Comp. 1	Comp. 2	comp. 3	Comp. 4
Standard Dev.	2.2924	1.1345	1.0330	0.9493
Prop. of Variance	0.5255	0.1287	0.1067	0.0901
Cumulative Prop.	0.5255	0.6542	0.7609	0.8510

TABLE IV: Principal components and coverage of the data.

As shown, with just the four principal components, we are able to cover a total of 85% of the cumulative proportion of variance of the dataset. Thus, we have reduced the dimensionality by 50% (from ten predictive variables to four principal components.) Next, we define how each principal component is calculated. Table V shows the coefficients for each predictive variable in from the original set of features. For each component, we may calculate the score by using a linear combination of the coefficient multiplied by the respective predictive variable, as described by the equation:

$$score_j = \sum_{i=0}^{10} coefficient_i^j \times value_i.$$

Predictive Variable	PC #1	PC #2	PC #3	PC #4
Own Wall Posts	-0.278	-0.169	0.401	-0.204
Friend Wall Posts	-0.400	-0.198	-0.177	
Words Exchanged	-0.410	-0.202	-0.186	
Friend Count	-0.310	0.351	0.298	0.204
Traded Item Count	-0.172	0.319	-0.506	0.630
Common Apps.		0.499	-0.453	-0.691
Positive Words	-0.410	-0.199	-0.188	
Negative Words	-0.371	-0.233	-0.117	-0.180
Mutual Friends	-0.250	0.412	0.397	
Common Groups	-0.316	0.390	0.128	

TABLE V: Table of coefficients for principal components

D. Creating Human-Interpretable Component Labels

For each principal component, grouping the coefficients by their signs allows us to begin to reason about each principal component in more abstract and descriptive terms. Below, we analyze each of the 4 principal components' coefficients in order to gain an intuitive understanding of the high-level characteristics being represented by them.

1) *Engagement Index (Comp. 1)*: The coefficients are all of the same sign, except for the 6th predictive variable (Average Common Applications) which has a coefficient of zero, indicating its omission in the calculation of this component. The component focuses on the variables which involve high social or network interactions within Steam's social network, as some common applications might be single-player games which players do not interact with one another. It appears to indicate that this component generally deals with player interaction and engagement as a whole on the *Steam* network.

2) *Weak/Strong Tie Index (Comp. 2)*: Coefficients 1-3 (Intensity) and 7-8 (Emotional Support) are related by the same

sign. Coefficient 4 (Friend Count), 5 and 6 (Traded Items and Average Common Applications), and 9 and 10 (Mutual Friends and Common Groups) share the same sign, Intimacy, Reciprocal Services and Structural variables. The component points differentiates between players with closer relationships, versus players who have structural many friends. A notable result is the grouping of related predictive variables matched the categorizations by Gilbert et al [14].

3) *Trader/Gamer Index (Comp. 3)*: The variable coefficients relate Friend Wall Posts, Words Exchanged, Traded Item Count, Average Common Applications, Positive Words and Negative Words together (negative sign), and secondly relate Own Wall Posts, Friend Count, Mutual Friends, Common Groups (positive sign). The component appears to discern between players who actively comment on one another's profiles, against those who do not appear to interact publicly, but maintain high common interests and friends. Players who trade extensively on *Steam* tend to post more on one another's walls when leaving feedback after transactions.

4) *Critic/Compliment Index (Comp. 4)*: The only variable coefficients that this component covers are Own Wall Posts, Average Common Applications and Negative Words (negative sign) and Friend Count and Traded Item Count (positive sign). The component describes players who tend to post on their own profile walls versus people who simply engage with the system with friends.

With the resulting four principal components, we perform four-dimensional clustering on the dataset to identify clusters of player profiles according the principal components. Using the BIC score as our model selection measure, we obtain an optimal value of k=5 clusters (BIC=-1275). Fig 5 shows a biplot of the clusters projected on the top two principal components of Weak/Strong Index versus Engagement Index. The graph points are labeled with each player's status performance classification.

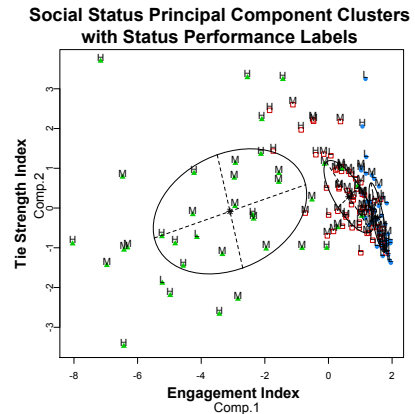


Fig. 5: Biplot of the dataset when plotted against the top two social status principal components.

We may represent the relationship between the social status and status performance clusters using a cross-tabulation table, shown in Table VI.

To quantitatively measure the association between the social status and status performance clusters, we used Cramer's

	LOW	MEDIUM	HIGH
Social Status Cluster 1	29	0	10
Social Status Cluster 2	15	4	20
Social Status Cluster 3	19	1	12
Social Status Cluster 4	2	14	18
Social Status Cluster 5	0	4	4

TABLE VI: Cross-tab of social status vs. status performance

V coefficient of association, of which we obtained a coefficient of $\phi_c = 0.449$. This indicates that positive association exists.

E. Predicting Status Performance using SVMs

The SVM model selection was evaluated using stratified 3-fold cross-validation grid-search. We evaluated the performance of two kernels, the linear kernel and the radial basis function kernel. We varied the C-value in the range [0.01, 0.1, 1, 10, 100, 1000] for both kernels, and changed the tolerance γ in the radial basis kernel in the range of [0.001 and 0.0001]. The optimal parameters for the SVMs were 1) radial basis function 2) $C = 100$ and 3) $\gamma = 0.001$. Table VII shows the results of the best performing trained model, fitted on the dataset. We obtained a classification accuracy of 61%, evaluated again by using stratified 3-fold cross validation.

	Precision	Recall	F-1 Score	#Samples
LOW	0.70	0.88	0.72	65
MEDIUM	0.66	0.59	0.62	23
HIGH	0.77	0.43	0.56	64
Average/Total	0.69	0.69	0.68	152

TABLE VII: Status Performance Classification Results

VI. DISCUSSION

In this section, we first discuss the implications of our methods in relation to game design, and how they potentially enable developers to understand more about how their players are distributed based on their social network characteristics. Next, we focus on the broader implications of our findings in relation to how it relates to real-world society, and characteristics of social behaviors of users.

A. Game Design Implications

As outlined in our results, the combined usage of clustering and dimensionality reduction over a set of features for a dataset of players allows us to identify categories of players based on their implicitly performed behaviors within a system. In our work, we focused on their interactions within, and with other players, in a social network. Fig 6 is a biplot of the players against social status principal components 1 (engagement index) and 3 (trader/gamer index). By observing the grouping and directions of the predictive variables (red arrows) along each axes, the players can be categorized along these principal component traits. For example, the y-axis is the trader/gamer index (principal component 3) which we identified earlier, and we are able to see which players (e.g., #69, #92 and #117) are most representative traders within the dataset. Using such methods and knowledge of the actual distribution of players, designers are then equipped to make more informed decisions, which are not based simply on prior assumptions of how the players might be distributed or categorized.

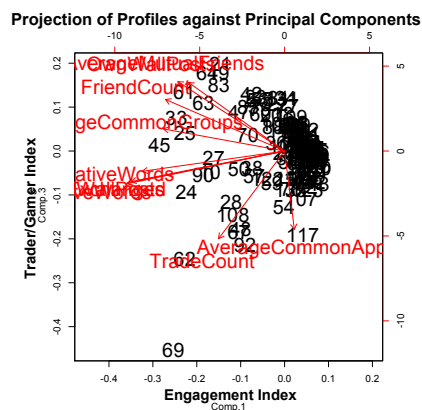


Fig. 6: Biplot of the dataset of players, projected against two principal components.

B. Social Implications

It is also important to consider implications related to social issues that might arise out of computational identity representation systems, especially with the high levels of interaction that occur between players, as well as with developers. Inference regarding a player’s real-world identity and preferences can be correlated with their behaviors in virtual worlds including avatar creation and customization (and vice versa). Also, the creation of items for sale and distribution in a virtual environment has similarities to the construction of value of physical items in the real world. Creating items for distribution in a virtual environment has similarities to the construction of value for real-world items. Looking at hats in TF2 based upon factors such as mode of acquisition, promotions by developers, monetary value, and so on parallels real world phenomena, such as the appeal of designer or limited edition goods. One can examine the different categories of people who seek to acquire particular virtual items or classes of virtual items (e.g., people with the means to seek out expensive items, people who care about aesthetics, etc.) and predict how they might perform status in a gaming/virtual world. In constructing virtual economies, consideration of social effects must go beyond enhancing or balancing gameplay, and should include sociological issues such as privilege and marginalization.

VII. CONCLUSION

In this paper, we have presented an approach to modeling player preferences quantitatively using a player social networking profile and taste performance in avatar customization. Our first system, the *Steam Player-Preference Analyzer (Steam-PPA)*, collects data from players social networking data on the *Steam* platform, as well as avatar customization data in the multiplayer online game *Team Fortress 2 (TF2)*. Our second system, the *AIR Toolkit Status Performance Classifier (AIR-SPC)*, uses machine learning techniques to create a model of the data, and can be used to perform prediction of player status performances. We construct models of players’ status performances by calculating the real-world monetary values of the virtual items (hats) associated with the virtual-character and belonging to the players. We showed a correlation between the value of a player’s used and collected hats, and illustrated

the effects of clustering to divide the player space into separate categories of status performance.

The *Steam-PPA* system also presents an approach to obtaining variables used for estimating tie-strength in the social network Steam. Our work also suggests Principal Component Analysis (PCA) as an effective technique to reduce the dimensionality of tie strength variables into a smaller, abstract set of social value principal components which still describe the original dataset. With information from two different domains (a social network and a game), we showcase the effectiveness of using Support Vector Machines (SVMs) in learning to classify status performances using social statuses. This main result of the paper highlights the existence of a strong relationship between a player's real-world identity and virtual identity within games. We hope to motivate designers of computational identity systems in games and social networks to consider the importance of providing adequate technologies for users of such systems and to remember to consider the effects of any coupling between real-world and virtual identities, through games, social networks, and most importantly, integrated hybrids of both.

VIII. FUTURE WORK

There are several ways our efforts could be extended. One way to gain more insight into the effectiveness of our approach would be to aggregate more publicly available data, and to extend the number of tie strength predictive variables beyond the ten used in this paper. Extending *Steam-PPA* to collect different types of player data (e.g., achievements games), gameplay data (e.g., players' favorite character classes, proficiency levels), and distribution data (e.g., method of hat acquisition) would allow us to get more diverse insight into the relationship between performance, social structures and player behavior. This could improve the machine learning components of *AIR-SPC* to identify more representative clusters using k-means, and provide more training data for supervised learning.

An interesting extension would be to investigate whether social values can be predicted from status performance for players. This reverse classification would provide insight into how gameplay in the virtual world translates into the world of social networking (which many users consider to be close to the real world). It would allow us to better study the relationship between identity and behavior in-games and in relationships on social networks. We also plan to plan to use different ways of performing sentiment analysis, one of which is to use the Linguistic Inquiry and Word Count (LIWC) database for categorizing word emotions. We also believe that the *AIR-SPC* system, and the techniques and approaches outlined in this paper, can be applied to other integrated platforms. For instance, we could switch the source of social networking data from *Steam* to Facebook. One could also use different games, whether distributed by *Steam* and with an official API, which *Steam-PPA* could be extended to work with, or a separately distributed game.

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