Portray Product Experience by Expert Reviews—
Video Game Classification on In-gaming Experiences

Course Project of MACS 30200

Chih-Yu Chiang

Abstract

How can subjective experiences be logically portrayed? For experience-intensive products, such as video games, where graphic quality, game specifications, and other traditional metrics are deficient in illustrating the diverse gaming experiences players seek for. Product genres (first-person shooters, role-playing, puzzle games, etc.) may serve as one common and simplistic manner of categorizing product experiences. However, they capture only a superficial form of one's interaction with the product and are hardly indicative of the rich depth of product experiences that one may be exposed to as a user or a player. In this research, I employ video games and their review articles to demonstrate a new analytical scheme that describes product experiences through corresponding product critique reviews, where information of the experiences is extracted via computational content analysis approaches. With a classification model, this scheme connects the real product experience, retrieved from a survey, with experiential information, extracted from the review articles, to provide quality measures for the abstract product experiences in a much objective and cost-effective way.

Contents

Introduction

Many products in the past centuries found their way into diverse consumer pools based on their objective functionality. We expect automobiles to carry passengers, laptops to run application software, or cameras to capture the beauty of the world. Mostly, their functions are tangible and quantifiable. We depend on quantified measures to evaluate the products, to form judgments, and to develop proper response actions—as a business, to plot a product strategy; as an individual, to make purchase decisions. We rely on the horsepower of a car to determine its capability of shipping heavy freight, the RAM size of a laptop to weigh its capacity in completing complex computational tasks, and the pixel count of a camera to assess its utmost photo quality. With clearly measured criteria of the functional specifications, for these evaluations, minimal difficulties could be involved.

Yet, it becomes far harder to evaluate products when their attributes are intangible, unquantifiable, or where some element of subjectivity is involved. Movies, books, and video games fall into this product category—what we call experiential products. In the last decade, increasingly more products shift from providing consumers only physical functions, to delivering them both physical and mental satisfactions. Businesses incorporate cultural and experiential part in their products, such as brand stories and social elements, and include psychological interactions with the customers throughout the consumption to deliver proper emotions, sensations, and memorable events. Rather than separate fulfillments of single functions, individuals tend to consider product consumption an integral experience.

How can subjective experience be portrayed substantively? Some experts rely on the product genres, such as science-fiction novels and action movies. While loosely capturing the general flavor of a product, traditional genres are mostly superficial and barely quantifiable. Others acquire experience information by interviewing and surveying the users. However, interviews and surveys on the experience are hardly organized and difficult to make effective arguments, because the lack of a universal consensus of what constitute an experience to be applied to structure the process of acquiring the experience information. Furthermore, the ways of involving the end users are often costly, not to mention the subjectivity carried along with each of the individuals. All these complicate the acquirement of a complete and precise understanding of the product experience and hinder the evaluations to be objective, to be applied across individuals, products, and product categories. They also illustrate the inadequacy of the current ways of assessing product experience—a new proxy for describing the experiential formation of a product is in demand.

Answering this need, this research proposes a new analytical scheme that describes product experience through product critique reviews—evaluative texts of particular products, by customers or opinion leaders with expertise in these certain types of products. They indite the reviews to express, store, and exchange thoughts and judgments regarding their own experience in a product.

In this study, video games and their review articles are applied to demonstrate this new scheme. Review articles for video game products have always been abundant. As a typical experiential product, every video game is in itself a contained local landscape that structures the virtual experience of the players. Within a game world, there are social structures, e.g. multiplayer elements and interactions with non-playable characters and the like; cultural systems, e.g. in-game society customs and jargon; and material resources: e.g. virtual currency and carefully catered environment of a game. The luxuriant virtual ecosphere interacts with players to form the video game experience, which is hardly described by traditional measures such as video game genres, which emphasize only the ostensible forms of gameplay.

Literature Review

Experience and Experiential Product

Experience is at the heart of this research. Defined by The Oxford English Dictionary, *experience* is "the actual observation of events" and "the state or condition being a subject is consciously affected by them (the events)" (OED Online, 2017a). The definition was added by some scholars, where the *events* have to be meaningful and actually encountered by the subjects to form an experience (Hassenzahl, 2011). Some others further stressed the meaning of a *state*, which has to be generally unphysical, such as fantasies, feelings, and fun (Holbrook & Hirschman, 1982). In the field of product design, among different types of states, *affect* is particularly stressed. Several studies tackled on the issues such as how to evoke proper emotions during users' interaction with a product (Forlizzi, Disalvo, & Hanington, 2003; Havlena & Holbrook, 1986; Ho & Siu, 2012). Applying the definition in video game context, in this research, video game experience is thus described as a subject's interaction with events in video game worlds, along with the mental states—emotions, feelings, memorable moments, and others—aroused with the interaction.

For video games and other products dominantly emphasize on their consumption experience—the experience occurring during their consumption—scholars recognize them as the *experiential products* (Cooper-Martin, 1991). This concept can be linked back to products' experiential attributes. The experiential attributes distinguish themselves from utilitarian ones (Zeithaml, 1988); during product consumptions, experiential attributes are the symbolic, hedonic, and aesthetic natures of a product (Holbrook & Hirschman, 1982)—the natures lead to a pleasure of product use, such as feeling confident, secured, and exciting by the users (Jordan, 1998). Emphasizing experiential attributes, experiential products developed several distinct characteristics. Experiential products stress on a fluent sensory and affective information delivery (Brakus, Schmitt, & Zhang, 2014); in contrast with utilitarian products, they enlist different paths of customer evaluation, which influences product judgment of the customers (Brakus, Schmitt, & Zhang, 2007). Indeed, for experiential products, customer satisfaction is correlated to their entire consumption experience, rather than single attributes or separate consumption stages (Bassi, 2010). Some typical examples of experiential products are films (Bassi, 2010; Cooper-Martin, 1991), music (Lacher, 1989), and video games (Tschang, 2005).

In the eyes of some scholars, video games are purely designed experiences (Squire, 2006). During their consumption, they provide little to none physical rewards. Instead, they create virtual events to interact with the players, stimulating player mental states such as a sense of belonging to a virtual warrior guild or a friendship during virtual cooperative military operations. In general, a process of playing video games can be deemed as a course of attaining gratification, that is, positive experiences (Grodal, 2000). These pleasing experiences are empirically shown to be associated with players' game preference and amount of time they are willing to play the games (Johnson, Gardner, & Sweetser, 2016; Sherry, Greenberg, & Sherry, 2006; Zeigler-Hill & Monica, 2015), a relationship echoes experience's important role in video games as a type of experiential products. In fact, this relationship is formed because, through those experiences, players fulfill basic human psychological needs (Ryan & Deci, 2000). This satisfaction of needs serve as psychological motives and motivates individuals' continuous consumption in those products (Hassenzahl, 2008)—the very reason why people play video games.

Traditional Ways of Portraying the Experience

While relevant research is abundant in the product experiences, our understanding is still limited. I deem the problem twofold. First, in early research, product experiences are examined primarily based on their traditional genres (e.g. Billieux et al., 2013; Fuster et al., 2014; Gao et al., 2013; Kim & Ross, 2006) and platforms (e.g. Klimmt, Schmid, & Orthmann, 2009; Mccauley, 2014), which, oftentimes, do not describe well the experiences consumers can have with a product. For example, both first-person shooter games, *Counter Strike* stresses on team cooperation while *Half-life* provides strong story-telling elements. This difference leads to distinct in-game experiences of the two games. The discrepancy between video game experiences and video game genres was empirically displayed in Park, Song, and Teng's research, where player personality predicts players' preference in psychological motives, such as achievement and relationship, which are reflected in the experience provided in the games, but not their preference in game genres (Park, Song, & Teng, 2011).

Second, most, if not all, of the early literature on product experiences applying methods of surveys and interviews. In traditional surveys, questions and answer options are limited to researchers' decision. This limitation could harm research's completeness especially for those still in their exploratory phase and without an overarching theory, such as studies in video games' psychological motives as their experience dimensions (Oswald, Prorock, & Murphy, 2014; Poels, de Kort, & Ijsselsteijn, 2012; Quick, Atkinson, & Lin, 2012). On the other hand, open-ended questions and interviews suffer from the fallacy that they have to assume the customers know well the experience and the psychological constructs behind. "A lot of times, people don't know what they want until you show it to them," as quoted from Steve Jobs (Mui, 2011), the answers researchers seek for from the customers are often tacit and cannot be recognized by ordinary customers without specific training and sufficient cognitive processing. The customers' incapability of responding to the questions can impair the analyses based on these answers.

To provide a more inclusive and objective alternative, this research identifies the experience elements based on an entire English lexicon and, through these elements, extracts experience of specific products from expert review text via techniques of content analysis. This research utilizes the natural connection of languages and the experiences as a new approach in portraying the product experiences.

Experience in Text

To perceive the world, human develops languages (Gibbs, 2003). Languages are not only a product of speech but also an expression of human society's cultural conventions (Saussure, 1959). Interpreted in the languages, these conventions interplay with human cognition, influence how people see themselves, other things, individuals, and the society (Carley, 1994; Levi-Strauss, 1976). Therefore, from the languages, human behaviors and the social facts can be observed (Saussure, 1959). This observation can also go beyond tangible realities. Through law, myth, and other linguistic products, attitudes of people, values of a society, and cultural structures behind all the tangibles and intangibles can be examined. Researchers analyzed linguistic patterns to inspect human conceptual thoughts (Gibbs, 1994; Lakoff & Johnson, 1980) and answer social questions (Evans & Aceves, 2016). At a macro level, scholars detect cultural, linguistics, and technology trends in a society (Michel et al., 2011); at a micro level, they identify individual opinions (Pang & Lee, 2008) perhaps from on-line posts for a stance in a debate (Fermín L. Cruz, Troyano, Ortega, & Enriquez, 2011) and from customer comments for features of a product (Duric & Song, 2012) and customer opinions corresponding to those features (Tian, Xu, Li, & Pasi, 2014; H. Zhang, Sekhari, Ouzrout, & Bouras, 2016).

To mine those customer comments, one common approach is sentiment analysis (M. Zhang & Ye, 2008). From product reviews or relevant texts, sentiment analysis extracts sentiment concepts toward a given topic, such as a writer's positive or negative valance to a product (Agarwal & Bhattacharyya, 2005; S. S.-M. S. Kim & Hovy, 2004; Yi, Nasukawa, Bunescu, & Niblack, 2003). From the meaning of each of single words and of higher level linguistic patterns shown in the texts, this method evaluates semantic intimacy of the sentiment concepts and the topic, for example, how much a writer like or dislike a product (Jadi, Claveau, & Daille, 2016).

Advanced sentiment analyses observe more complex concepts, such as affects (Cambria, 2016) and product consumption experiences (Xiang, Schwartz, Gerdes, & Uysal, 2015). Human experiences are stored, exchanged, and construed with the use of languages (Halliday, Matthiessen, & Yang, 1999). From languages, these experiences are ready to be discovered with a proper approach. More than evaluating the value of a product, reviews help to convey product experiences to its readers. They typically relay the various experiential dimensions of a product. For example, the kinds of in-game systems a game has, the various challenges players will encounter, storylines, and the various intricacies of the game's social world.

To label the types of experience and the specific types of experience conveyed by each product, or video game in this study, I rely on the ideas of sentiment analyses and their linguistic foundations. To identify typical experiences, I curate an experience lexicon, which attempts to contain all potential words connected to human experiences. In studying various linguistic concepts, traditionally, researchers adopt similar approaches by manually curating concept specific lexicons, for example, a lexicon with vocabulary expressing positive sentiments and another with words representing negative ones (Das & Chen, 2007; Hurst & Nigam, 2004; Taboada, Brooke, Tofiloski, Voll, & Stede, 2011; Yi et al., 2003). However, with more than two-hundred thousand English words extant (OED Online, 2017b), the lexicon curation process is always extremely time-consuming. Manually curated lexicons also suffer from subjectivity problems because they depend largely on each scholar's own judgment.

In this research, I build the experience lexicon through a modified approach, identifying the vocabulary of experiential concepts by the words' definitions in accredited dictionaries. In a study of linguistic sexual equality, this approach was first adopted by Bolukbasi and his colleagues. They, for instance, searched female in all word definitions in a dictionary to locate those words contain the meaning of *woman*, such as MOTHER, QUEEN, or ALUMNA (Bolukbasi, Chang, Zou, Saligrama, & Kalai, 2016). In this research, I apply this inverted dictionary search in *Webster's Unabridged Dictionary* to identify the experiential words—words related to an experience. Such as FEEL, EMOTION, and EVENT, 23 keywords are used in the search, resulting in two thousand experiential words constituting the lexicon. The experience lexicon is then expanded by WordNet, a respectful lexical database curating cognitive synonyms by scholars from Princeton University (Agarwal & Bhattacharyya, 2005; Ohana & Tierney, 2009). To ensure the curated lexicons complete, expansions by WordNet are common and proved useful (F. L. Cruz, Troyano, Ortega, & Enriquez, 2011; Verma & Pushpak Bhattacharyya, 2009) and often seen in sentiment analysis approaches (e.g. Andreevskaia & Bergler, 2006; Poria et al., 2012).

With the experiential vocabulary, I apply Word2Vec (W2V) algorithm (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013) for identifying the semantic relationship of the lexicon and the review articles. Accepting the review articles as the input, the W2V algorithm supplies a high-dimensional space that representing semantic similarities between words apropos of linguistic conventions of a specific field exemplified by the input articles. Each unique word within the corpus is located in the W2V space with a unique word vector, which, in turn, can be used to develop the document vector of each article (Le & Mikolov, 2014). A document vector is the context memory of all words constitute this specific document text, and, therefore, represents a general semantic orientation of this article. As expert reviews are linguistic concretizations of experience delivered in the corresponding video games, their document vectors are deemed as the integrative experience features of those games. The W2V embedding is computationally efficient and effective in capturing text semantic relationships from the word structures expressed in the article. It is commonly employed in content analyses of academic research (e.g. Suárez-Paniagua, Segura-Bedmar, & Mart'inez, 2015) and industrial applications.

Method and Result

To connect video game experiences to the corresponding expert review texts, in this study, I implement a classification model with the reviews in predicting video game experiential genres, the general categories of video game experiences. To start with, potential experiential genres of 50 selected video games are identified through a survey consulting real players. Meanwhile, specific experience features of each video games are addressed in corresponding expert review texts. These features are taken as input of the classification model to predict experiential genres of the selected games acquired from the survey. Next, the model error rate is reviewed to confirm a sound connection between these two constructs, the video game experiential genres and the review texts, where the input features obtained. One step further, this classification model is applied to other games not included in the original survey to obtain predicted experiential genres. These predicted genres are thereafter examined to further confirm the established connection and to identify experience features best distinguishing, or portraying, the underlying genres.

Data

Response Variable - Experiential Genre

Experiential genres are game categories premised upon experience delivered in video games. Identifying those genres, a survey is conducted with a small subset of video games through Amazon Mechanical Turk (MTurk). The games used in this survey are hand-picked with a standard of the accumulative sales upwards of 4 million titles and are across game platforms, e.g. Play Station and Wii, and traditional video game genres, e.g. First-Person Shooter and Role-Playing Games. These criteria are applied to ensure the representativeness and the diverse of the video game experiences. 50 video games are chosen and hereon known as "core games", including popular titles such as *Diablo III*, *Angry Birds*, *Half-Life 2*, *New Super Mario Bros*, *League of Legends*, and *The Elder Scrolls V: Skyrim*[1].

[1] A full list of the core games is provided in Appendix A.

With 350 participants[2], the survey collects 6,990 experiential resemblances in a triplet form—the relative similarity of game A to B and to C[3]. These triplet-resemblances are built into a high-dimensional space via the t-Distributed Stochastic Triplet Embedding (t-STE), where distances between each game preserve the similarity of the games' experiences[4]. This algorithm is specifically adjusted to the task of extracting the information from triplet comparisons, and outperforms Generalized Non-Metric Multidimensional Scaling, Crowd Kernel Learning, and other existing techniques on the specific triplet data form. 25 dimensions are extracted from the embedding according to the pattern of the error rate, the percentage that the triplet responses are wrongly described by the Euclidean distances between the focal objects[5]. These 25 dimensions retain an 80% precision rate of describing the video game similarity reported in the survey (Figure 1).

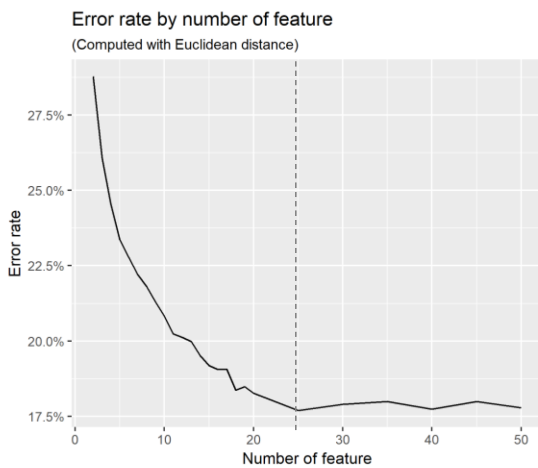

Figure 1. t-STE Error Rate by Number of Features

With the game vectors in the embedded space, I conducted a hierarchical clustering via the Ward variance minimization algorithm to group the core games into game experiential genres. To determine a proper number of clusters, the elbow method is employed. In Figure 2, the blue line is the distance growth between each merge; the orange line represents the distance growth acceleration, the first order derivatives of the blue line. The ideal number of clusters are suggested to be the peak growth acceleration at two clusters, then five, and seven. Considering the meaningfulness of the acquired clusters, the seven clusters were selected[6] to represent the seven experiential genres in the later part of this research.

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[2] Demographic description of the survey participants and the triplet distribution is provided in Appendix B and D, respectively.

[3] For example, "based on your in-game experiences, is *Half-Life 2* more similar to *RollerCoaster Tycoon* or *Metal Gear Solid*?"

[4] Projection of the core games is provided in Appendix B.

[5] For example, the embedded information is deemed wrong when the survey response claims that *Half-Life 2* is more similar to *Metal Gear Solid* than *RollerCoaster Tycoon*, but, in the embedding space, the distance between *Half-Life 2* and *Metal Gear Solid* is, contrarily, longer than between *Half-Life 2* and *RollerCoaster Tycoon.*

[6] The full cluster result is provided in Appendix E.

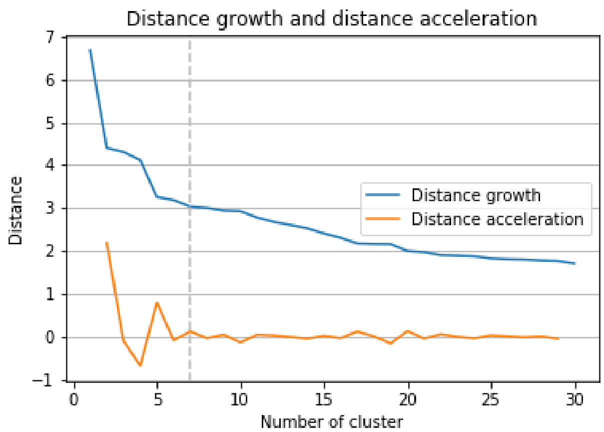

Figure 2. Distance Growth and Distance Acceleration of Clustering Merges

The clusters are projected with the two-dimensional t-STE vectors, with the colors representing the genres, as shown in Figure 6. In the projection, the genres are geographically distinct. This indicates the satisfied quality of the clusters, each characterizes a distinct stress in the experiences.

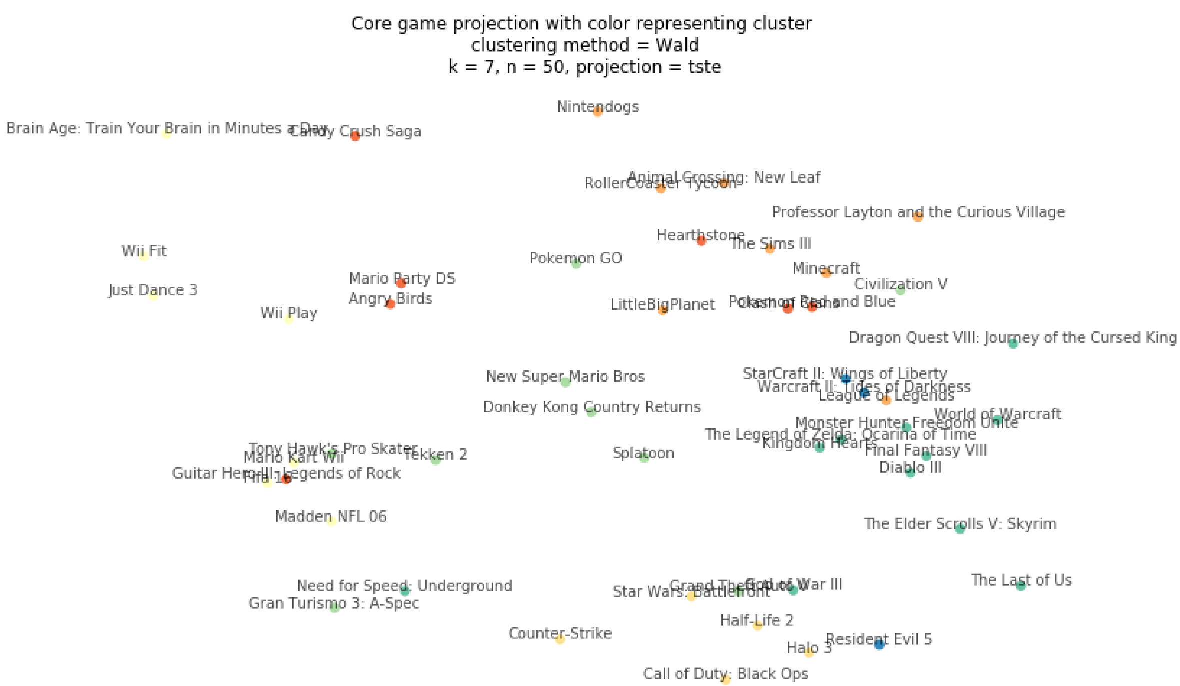

Figure 3. Core Game Projection with Cluster Labeling

For example, Genre #2 (the orange genre) includes traditional simulation games, as well as several MOBA and puzzle games, expressing a creation, or creative, experience of the games. This genre includes eight core games as listed in Table 1. *Nintendogs*, *RollerCoaster Tycoon*, and *The Sims III* are the traditional "simulation" games that simulate a specific context or event. Such as *RollerCoaster Tycoon*, it provides a context for the players to operate a virtual theme park, where players decide what rides to be introduced in the park and, with them, how to allure customers to make more profit to be used in developing this theme park further. The simulation feature of the games provides a great freedom and, intuitively, requires the players to be creative to succeed in those games. Interestingly, four other games of this orange group, *Professor Layton and the Curious Village*, *Minecraft*, *League of Legends*, and *LittleBigPlanet*, each belongs to a different traditional video game genre. *Professor Layton and the Curious Village* is a puzzle adventure game, *Minecraft* is a sandbox, *League of Legends* is a MOBA type game, and *LittleBigPlanet* is a platformer. However, they do share the similarity in the experiences they deliver—they all stress on the creative experience in their gameplay. For instance, although a platformer game, *LittleBigPlanet* is really praised by its openness in allowing players to create and share player customized levels. On the other hand, *League of Legends* features its 136 champions, each with a different appearance, skills, and battle characteristics. To succeed in the game, players are required to operate each champion and cooperate with other champions creatively—simply consider the number of combinations of champion selection by five players in a team, each with 136 possibilities: the 136 to the power of five!

Table 1. Core Game List of Genre #2

The Sims III	League of Legends
RollerCoaster Tycoon	Animal Crossing: New Leaf
Nintendogs	LittleBigPlanet
Professor Layton and the Curious Village	Minecraft

Predictor Variable - Experience Feature

Game experience features are specific experiences delivered in a game. In this study, they are extracted from an expert review corpus, compiled from articles of three major game information websites, GameSpot, GamesRadar, and Polygon. The corpus total includes 15,727 English reviews, covering 11,724 unique games in the last four decades, and amasses a total of 15-million words of analysis. Video games represented by the reviews are across platforms, traditional game genres, and, apparently, video game developers and publishers. The review database for the 50 core video games is specifically expanded to include game reviews from other information websites, such as IGN, GameFAQs, and PC Gamer. The corpus of core game reviews, then, contains a total of 355 review articles. Each review article makes up one individual observation in the later model building.

For the entire review corpus, stopwords are removed using the NLTK English stopword dictionary; no stemmers and lemmatizers are used as to preserve the information from the sentence structures. A word cloud is provided (Figure 4), showing high-frequency terms of this corpus. Beside GAME, GAMEPLAY, PLAYER, and obvious top words belong to a video game corpus, LEVEL, SOUND, WEAPON, STRATEGY, ONLINE, MISSION, ENEMIES, COMBAT, CARS, and a bevy of other words together constitutes a strong “video game flavor” of the underlined video game expert review database.

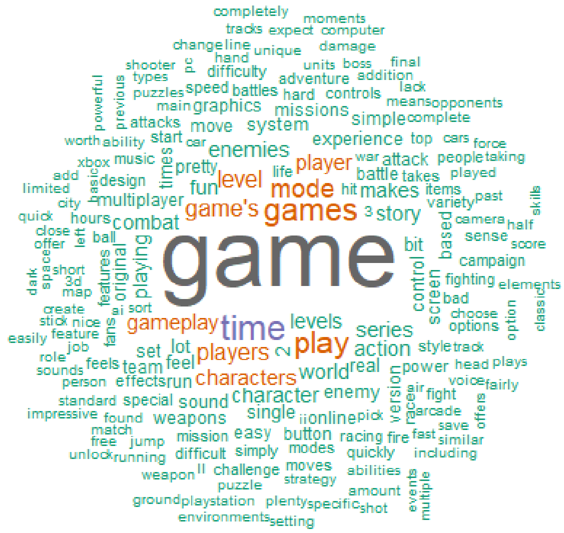

Figure 4. Game Cloud – Video Game Corpus

The corpus is then applied with the Word2Vec (W2V) negative sampling to provide a 300-dimensional space that representing semantic similarities between words apropos of linguistic conventions of the video gaming field. Based on this embedding space, two approaches are adopted in acquiring the features. One utilizes the Doc2Vec (D2V) algorithm to acquire document vectors, each denotes the semantic position of a review article in the W2V space. Out of the vectors, the value of each dimension is taken as an experience feature of the corresponding game. Another employs a document's cosine similarity, in the W2V space, of each "experience concept group" as the feature.

The concept groups are clusters of 30,396 experience keywords, identified through reversed searches of Webster Unabridged Dictionary and expanded by the WordNet synsets[7]. Some randomly selected sample keywords are shown in Table 2[8]. The keywords are clustered with the Ward algorithm into 10, 30, 100, 300, and 1000 concept groups, by their semantic meaning revealed through the Google News W2V space[9].

Table 2. Sample Keywords

ANIMAL	BILE	INTERJECTION	INSOLENT	NERVOUS	FUMBLE
TEMPERATURE	APATHETIC	EQUIVOCAL	DISDAIN	SCANDALOUS	FRONT
LOATHFUL	APATHETICAL	PRACTICALLY	INSTINCTIVE	DECLAMATION	AFFECTUOUS
DESIGN	NUMBNESS	RIVAL	ACUTE	USAGE	QUALM
ALIVE	FERVENT	REASONING	ACTION	IMPETUOUS	DELICIOUS

The produced keyword clusters are considered the "experiential concept groups" as they each gathers a set of semantically similar words and denotes an abstract experiential concept. For example, Group #292 (of the 300 clusters), containing the words shown in Table 3, conveys an experience about *foods*, perhaps *frolic foods*, as many of them are not only foods, but foods connected to parties, feasts, and splurges. On

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[7] The process of identifying the keywords is described in Appendix F in further detail.

[8] More examples are provided in Appendix G.

[9] Here a different word embedding space is applied so that the extracted groups could represent more general and precise relationships between the experiential words, instead of their specific expression in the video game field.

the other hand, Group #11 contains a particular experience of military (Table 4), as the keywords include not only types of armed forces but also actions, equipment, and facilities commonly associated with the troops[10].

Table 3. Keyword Group #292

PICNIC	EGG	PEANUTS	ENCHILADA	SOIREE	CANDY	GRAVY	TURKEY
FETE	DOUGH	MACARONI	FALAFEL	FIESTA	BUFFET	SNACK	CEREAL
CHILI	SANDWICH	HAMBURGER	JAMBALAYA	PORK	MENU	BRUNCH	BARBECUE
CHICKEN	CUP	REFRESHMENT	LUTEFISK	APPETIZER	ENTREE	DINNER	BARBEQUE
BEEF	BREAKFAST	BRATWURST	PIZZA	GUMBO	BOWL	POTLUCK	SODA
MEAT	LUNCH	HOTDOG	SCRAPPLE	COOKOUT	FEAST	SUPPER	BEER
JUICE	SUDS	MILKSHAKE	TACO	CUPFUL	EXTRAVAGANZA	TEA	POPCORN
CHAMPAIGN	PEANUT	COFFEE	TAMALE	KETTLE	BASH	BAGEL	BURRITO
BUTTER	BREAD	SMOOTHIE	VENISON	COOKIE	QUART	BURGOO	BOLOGNA
TOAST	KOSHER	APPLESAUCE	FRIES	LUAU	COOKBOOK	TURKEY	SHINDIG
POT	MEAL	RECIPE	TOASTING	HOAGIE	HUMMUS	BOLOGNA	

Table 4. Keyword Group #11

ENLISTMENT	MARKSMANSHIP	MATERIEL	BATTALION	BREVET	COUNTERFIRE	NAVY
SUBMARINE	SEAMANSHIP	AIRCRAFT	NAVAL	AVIATION	GENDARMERY	WEAPONRY
REGIMENT	CALVARY	AIRCREW	OLYMPIAD	AIRMANSHIP	RECONNOITER	GUNNERY
NAVY	ENGINEERING	ROCKETRY	PLATOON	TECHNICAL	RECONNOITRE	CORVETTE
INSTITUTE	MISSILE	ANTIAIRCRAFT	EQUITATION	RECONNAISSANCE	ARTILLERY	WARSHIP
DEMOB	MUNITION	CAVALRY	AIRWORTHINESS	AIRFORCE	AMMUNITION	REENLISTMENT
OVERFLY	FIREBASE	GARRISON	RECCE	ARMY	AMMO	SEAWORTHINESS
AEROSPACE	DETACHMENT	PAYGRADE	RECONNOITERING	COASTGUARD	SPACEFLIGHT	FRIGATE
ROADWORTHINESS	RETRANSMIT	SUSTAINMENT	RECONNOITRING	MARINES	AIRSPACE	MARITIME
TROOPS	INTERCEPT	DESTROYER	STUDYING	REDCOAT	ROCKET	METEOROLOGIC
CONSTABULARY	TROOP	ARMY	RAINMAKING	EQUIPAGE	ORDNANCE	METEOROLOGICAL
CRYOGENICS	AERONAUTICS	PARATROOPS	REGIMENTAL	HORSEMANSHIP		
INFANTRY	ASTRONAUTICS	BRIGADE	OVERFLIGHT	ARMAMENT		

Classification Model

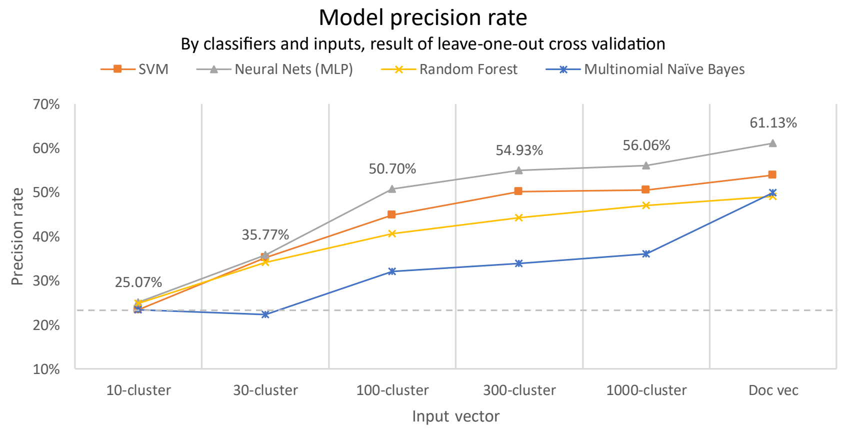
Training and Validation

Regarding the 50 core games, I extract experience features, from the 355 review articles, in predicting the games' experiential genres, identified in the survey, with multiple classification models. Both approaches of the experience features are applied with four classifiers: Support Vector Machine (SVM, with the linear kernel), Neural Nets (Multi-Layer Perceptron (MLP), with 100 hidden layers), Random Forest, and Multinomial Naïve Bayes.

Table 5 and Figure 5. Model Precision Rates

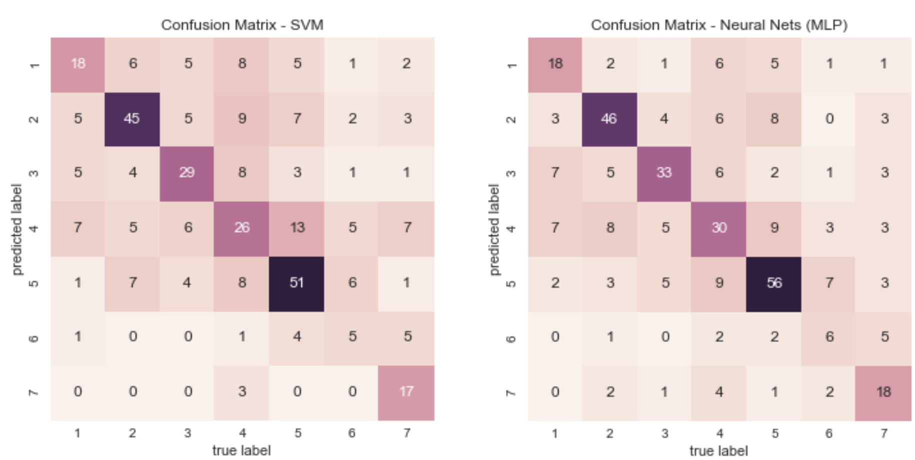
	10-cluster	30-cluster	100-cluster	300-cluster	1000-cluster	Doc vec
SVM	23.38%	35.21%	44.79%	50.14%	50.42%	53.80%
Neural Nets (MLP)	25.07%	35.77%	50.70%	54.93%	56.06%	58.31%
Random Forest	24.79%	34.08%	40.56%	44.23%	47.04%	49.01%
Multinomial Naïve Bayes	23.38%	22.25%	32.11%	33.80%	36.06%	49.86%

[10] A couple of other example concept groups can be found in Appendix H.



Of all combinations, general model precision rates are evaluated under the leave-one-out cross validation. Performance summary of all models is provided in Table 5 and Table 5. Among all models, the Neural Nets performs the best, with the document vectors as the input, topping a 61.13% precision rate in predicting the correct label out of the seven, a substantial improvement from the baseline of 23.38%[11]. This huge precision improvement confirms the connection between product review texts and the real experiences conferred in the product consumption and therefore the effectiveness of applying the product review texts in portraying the corresponding experiences.

Concerning performance of each specific experiential genre, the Neural Nets model functions well in almost all except Genre #6 (Figure 6). This performance characteristic can be observed in generally all model variations[12]. This is probably because Genre #6 is relatively underrepresented in the 355 review article sample, which contains 5.63% of the articles belong to this genre, compared to 23.38% for the largest genre. The smaller sample size may lead to insufficient information in the model training process for identifying robust features in the classification. More sample articles representing this genre are expected to be helpful in further improving the model's validity to this specific genre.



[11] By classifying all samples into the experiential genre with the most observations belong to it.

[12] Real cluster distribution of the core games is provided in Appendix I.

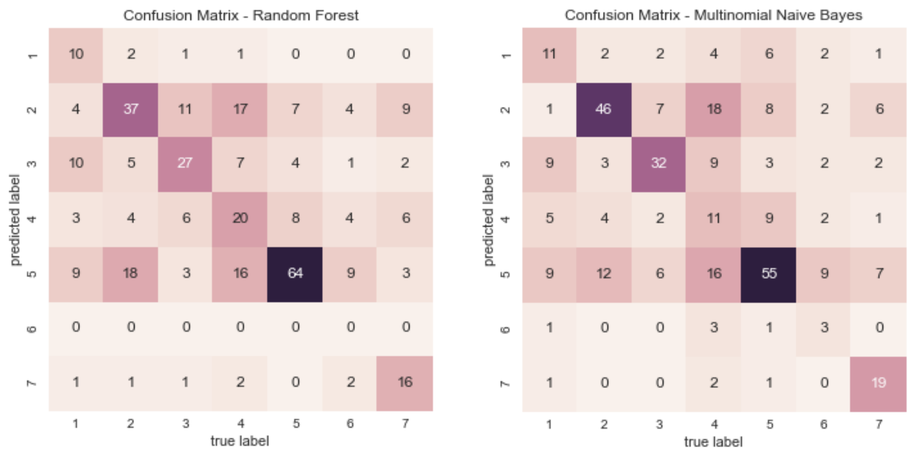


Figure 6. Confusion Matrices - Document Vectors as the Input

On the other hand, model precision rate increases as including more feature input in the model. Regarding the experiential concept groups, 10-cluster produces a result only close to the baseline. From 30, 100, and up 1000 clusters, all methods' precision rates rise with more clusters employed. However, the marginal increase diminishes dramatically after the 100-cluster input; the precision rate can be improved approximately only 5% with 10 times of the input clusters. More importantly, even with the 1000-cluster input, the model performance is inferior to the 300-feature document vector model, in terms of the general precision rate. Further analyses in this research will, therefore, adopt the document vector approach (300 features) with the Neural Nets (MLP) method in predicting experiential genres, while the genre characteristics will be defined jointly with features provided by the experiential concept groups to complement the lack of explainable meanings in the W2V document vector features.

Prediction of Non-Core Games

This best model is applied with the full 15,727 game reviews in the expert review corpus. This effectively estimates experiential genres for the 11-thousand non-core games. The results are projected with t-Distributed Stochastic Neighbor Embedding (t-SNE).

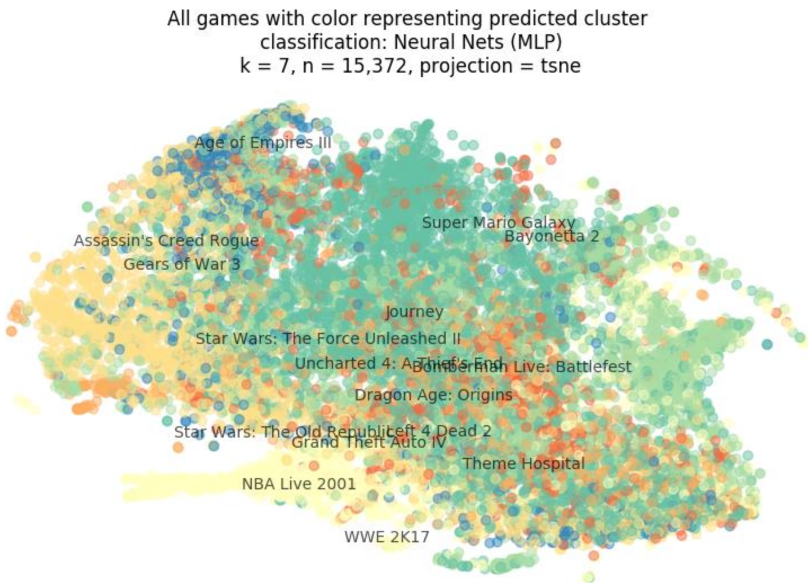


Figure 7. Non-Core Games Projection - Document Vectors as the Input

In general, the results are promising (Figure 7). Some popular games are randomly selected to be marked on the map. For example, both the sports type of games, *WWE 2K17* and *NBA Live 2001* are relatively near to each other and are clustered together with the champagne color. Some more third-person shooter and adventure games are gathered in the middle, including *Journey*, *Star Wars: The Force Unleashed II*, *Uncharted 4*, and *Dragon Age: Origins*. *Super Mario Galaxy* and *Bayonetta 2* are both a third-person action game and geographically close to each other, though with distinct world settings and therefore probably are clustered into different experiential genres.

We also gain superficial insights to the quality of the underlying model—it successfully captures the between-genre variation as shown by the observations' projected locations and provides further evidence of the connection between the review text and the in-game experiences. In this figure, observations of turquoise genre occupy the middle, with light green on the right, champagne color at the bottom, and blue and yellow on the left. Vaguely, red and orange observations gather in the lower middle section. Compared to the document vector model, the one with 30-cluster input (Figure 8) performs much worse as the turquoise and champagne color patterns are not as concentrated as in the document vector figure. In this 30-cluster model, clusters of red, orange, and light green are basically indistinguishable from each other and scatter across the entire space.

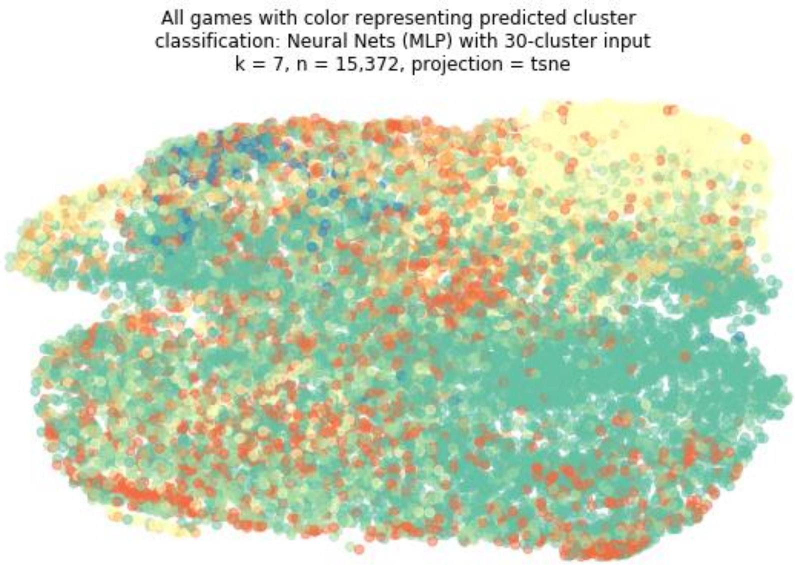


Figure 8. Non-Core Games Projection - 30-Cluster as the Input

Portrait of the Experience

With the validated connection between the review texts and the experience delivered in a game, we may describe the experience with measures developed in this study, the experiential genres, concept groups, and individual keywords. For example, by observing high-frequency keywords, we may savor the flavor of a genre. For Genre #1, we are impressed by the words like TIME, SERIES, and LEVELS (Figure 9), demonstrating the members' episodic gameplay style, for example, *Angry Birds* and *Candy Crush Saga*'s repetitive, periodic, and small game sessions. As for Genre #2, we have keywords like CREATE, WORLD, BUILD, and LIFE for the creativity-intensive games (Figure 10)[13].

Figure 9 and Figure 10. Word Cloud - Genre #1 and Genre #2

[13] Experiential keyword clouds of other genres are provided in Appendix 0.

We may also take advantage of a hierarchical structure among the measures—the genres can be portrayed with the concept groups, which are, in turn, impersonated by the individual keywords. For example, we could describe a genre via its scores (average cosine similarity) on particular concept groups. Shown in Figure 11[14], Genre #2 has the lowest score, among all genres, on Concept Group #11, the concept group denoting the *military force* experiences and comprises of keywords such as SUBMARINE, MISSILE, and BATTALION. Agreeing with our previous observations on Genre #2, these keywords properly signifies the opposite experiential nature of the genre's member titles such as *Minecraft* and *Animal Crossing: New Leaf*, which simulates a village community and, among it, the villagers' life. On the other hand, compared to Genre #2, Genre #1 scores higher on Group #168, the *music and dance* experience, and Group #292, the *frolic foods* experience[15], indicating its gaming experiences can be described closer to both of these concepts. This depiction can easily be confirmed by observing member games of Genre #1, including popular mobile games and party games such as *Angry Birds*, *Mario Party DS*, and *Candy Crush Saga*.

Likewise, Genre #2 also scores high on Group #292, the *frolic foods* experience, containing words such as PICKNICK, BUFFET, JUICE, and CANDY.

Group #168, with words CARNIVAL, JAZZ, MAMBO, GOSPEL, and JUKEBOX, which illustrates an experience of *music and dance*[16].

On the contrary, containing games such as *Angry Birds*, *Mario Party DS*, and *Candy Crush Saga*, the experiential Genre #1 possesses a higher score in Group #168 the *music and dance* and Group #292 the *frolic foods*, indicating the gaming experiences of Genre #1 games are closer to these concepts with high score, relatively to games belong to other experiential genres.

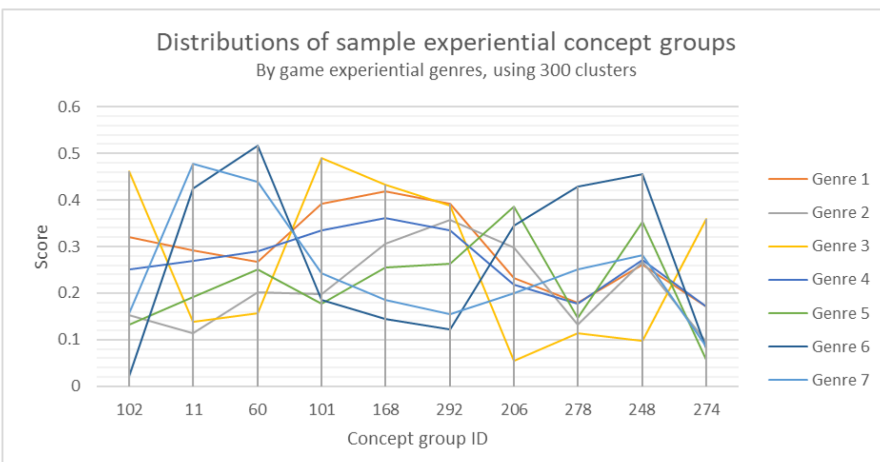


Figure 11. Distributions of Sample Experiential Concept Groups

In addition, I must note that while we can acquire the measures and scores for an experiential genre, as demonstrated, we can also compute them for individual games, with exactly the same method, for a more unambiguous portrait of the in-game experiences. Besides, the relationship between each game and the

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[14] The ten concept groups are selected with the largest within-group variation across different genres.

[15] The exemplified concept groups and the element keywords of each group are provided in Table 3, Table 4, and Appendix G.

[16] The exemplified concept groups and the element keywords of each group are provided in Table 3, Table 4, and Appendix G.

experiential genre is not a hard affiliation. From this model, each game's propensity to be categorized into each genre can be computed as well, and can be used to describe a game. This simplifies the direct description through the experiential concept groups. While the concept groups are many (e.g. 300 or 1000), applying them directly in illustrating the experiences could be unwieldy.

Discussion

Conclusion

Through this process, I first validate the effectiveness of employing the review text in portraying product experiences. In the classification model, I successfully predicted experiential genres extracted from the survey by the experience features identified in the review articles with a precision rate amount to 60%, compared to the baseline at 23%. The relationship between the two constructs is further discussed and observed in a large-scale experiential genre prediction for the rest of 15,000 game reviews representing games not employed in the original survey. This important connection expands our toolset in understanding product experiences with the expert review texts. This new approach is full of untapped potential particularly with the ripe of sophisticated natural language processing instruments.

This research develops quality measurements of the underlying product experiences, which is easily quantifiable and relatively objective in contrast with the traditional approaches as we largely reduce the subjective judgment of the end-users. For the starter, seven potential game experiential genres are identified through the triplet comparisons, which simplifies the involvement of the participants, helps to reduce fatigue on survey participants, at the same time alleviating the need to reconcile individuals' scales of similarity. This improves the measures' objectivity, compared to traditional surveys, which often involve more abstract questions to be answered and more researchers' personal judgment on selecting items to be asked in the surveys. In addition, from a semantic construct of the language, I propose a new strategy in identifying experience elements. Including the experiential keywords and their concept groups, they leverage the nature of human language development and explores the linguistic structure for a different approach in delineating human experiences, which are, furthermore, can be easily quantified and measured via the process demonstrated in this paper.

Moreover, this scheme demonstrates an approach that discerns product experiences in a much economical way because of less direct involvement of interacting with the users through surveys, interviews, and the kind. The full-scale application of the classification model illustrates the in-game experiences of more than 11-thousand video games with only the review texts as the input, which can be easily and cost-effectively attained from the web, in contrast with conducting real player surveys and, along with it, all the financial expenses and logistics problems to be able to cover the 11-thousand video game titles.

Lastly, this process can be generalized and applied to other experiential products. Our methods of identifying experiential keywords, doing triplet surveys and embedding, and tagging the game items by their review texts can be easily replicated with other consumer products that also are heavily experience-based. Movies serve as an excellent example of an experience-based product. With more and more filmmakers using 3D and even 4D technology, there is no doubt that movies, like video games, are at the forefront of challenging the frontiers of experience generation. Movies are also widely reviewed and discussed in the news, and through reviews and blog articles. This serves both consumers and developers well, as producers can tailor their games/movies to specific audiences, and audiences can easily know their game/movie preferences, thus making more optimal choices.

Limitation and Future Direction

Several refinements should be considered in future studies. First, expanding the inputs would make our model much more robust. For example, augmenting the core game set beyond 50 could provide additional useful information to examine the experience in further details. Increasing the number of review articles per game will also provide us with a more thorough view of the experiences of the specific games. the basis of our predictive model fundamentally hinges on game reviews, which average 1,170 words. It is unlikely that a single review with this length from one person's perspective would be sufficient to describe all the experiential elements within a single game. We would expect the model's prediction ability to be improved by including more than one article per game as more reviews coming from different sources covering the diverse features of a game and thus the comprehension of the in-game experiences.

Second, with regards to the experience-based word clusters, more research needs to be conducted to add in quality keywords that associate to experience and filter out those misrelated ones. We began to collect the keywords relating to experience based on 25 seed-words: including EMOTION, FEEL, EXPERIENCE, ENCOUNTER, and SENSATION. These were simply terms that came to our minds in trying to describe elements of a process of "experiencing". In other words, this was still a rather arbitrary process, and we believe that it can be improved if we used a more linguistically sound procedure that could churn out relevant experience-based vocabulary. As with finely calibrated vocabularies, we can create more meaningful experiential groups to better capture the "experience space", sieving out the noise while improving the predicting capability.

Third, the model is not restricted to a classification one. Other types of models can also be implemented for different purposes. For example, when sufficient training sample is provided, we may consider applying the review texts directly in predicting the score of the games on each experiential concept group via a Neural Nets regressor or a Random Forest regression analysis. This prevents information loss during the condensation from the t-STE vectors into the experiential genres while introducing more noise into the model, which has to be counteracted by a larger sample size. On the other hand, concerning the classification model itself, we might also be able to improve the model performance by modifying the underlying Neural Nets classifier with algorithms more sophisticated than the simple MLP structure.

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Technical Appendix

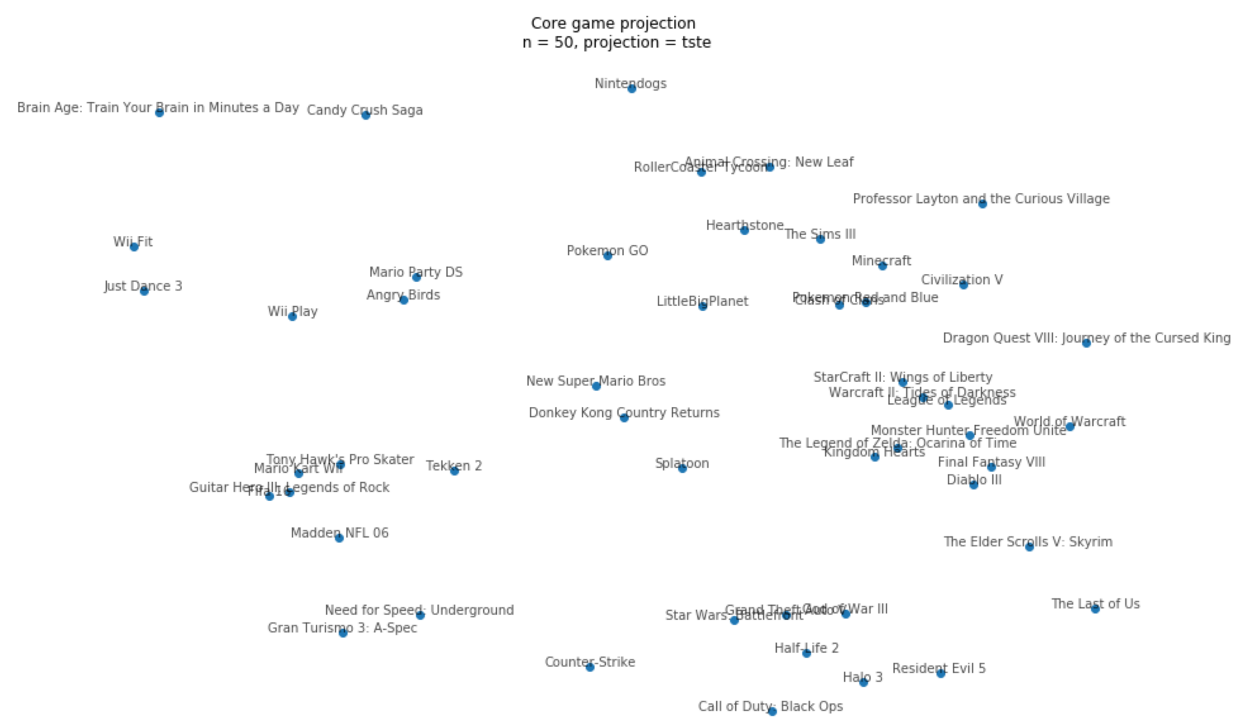
A. Core game list

The full list of 50 core games used in this study.

Diablo III	Brain Age: Train Your Brain in Minutes a Day	The Elder Scrolls V: Skyrim
Gran Turismo 3: A-Spec	Professor Layton and the Curious Village	Pokemon Red and Blue
Fifa 16	Half-Life 2	Civilization V
RollerCoaster Tycoon	Angry Birds	Call of Duty: Black Ops
Warcraft II: Tides of Darkness	The Sims III	Grand Theft Auto V
Madden NFL 06	Resident Evil 5	The Legend of Zelda: Ocarina of Time
StarCraft II: Wings of Liberty	Star Wars: Battlefront	Monster Hunter Freedom Unite
Tekken 2	Wii Fit	Splatoon
Tony Hawk's Pro Skater	Counter-Strike	League of Legends
The Last of Us	God of War III	Mario Kart Wii
Just Dance 3	Halo 3	LittleBigPlanet
World of Warcraft	Hearthstone	Guitar Hero III: Legends of Rock
Pokémon GO	New Super Mario Bros	Candy Crush Saga
Wii Play	Minecraft	Kingdom Hearts
Animal Crossing: New Leaf	Final Fantasy VIII	Dragon Quest VIII: Journey of the Cursed King
Donkey Kong Country Returns	Mario Party DS	Need for Speed: Underground
Nintendogs	Clash of Clans	

B. Core game projection

A projection of the embedded experience similarity between the core games is shown below by the two-dimension version of t-STE embedding.



Games deliver similar experiences are generally exhibited close to each other. For example, *Wii Fit* and *Just Dance 3* stand besides as they both entail a lot of real body movement in their gameplays. *Need for Speed: Underground* is nearby *Gran Turismo 3: A-Spec* as they are both car racing games simulating the real-life physics and environments. Interestingly, *Mario Kart Wii* is located almost in the middle of the mentioned two groups. As traditionally, *Mario Kart Wii* can be categorized as a car racing game, it, indeed, provides an experience distinct from the ones in conventionally car racing games, such as *Need for Speed: Underground* and *Gran Turismo 3: A-Spec*. Obviously, *Mario Kart Wii* requires more real body movement involved and stresses more on the spirit that, through it, multiple players can have fun together, just as what *Just Dance 3* emphasizes. The result described in the projection strengthens our confidence that the t-STE appropriately captures the experience similarity between the focal games.

C. Survey demographic summary

The demographic data contains information of 215 participants out of 355. Information for the rest of respondents is unavailable due to a survey design change.

	Age	Education	Income
Min	19.00	1.00	1.00
Max	59.00	8.00	9.00
Mean	30.90	3.94	4.76
Median	30.00	4.00	5.00
Std	7.29	1.32	2.10

Race	
White	174
Black or African American	14
American Indian or Alaska Native	0
Asian	12
Native Hawaiian or Pacific Islander	0
Other	2
More than one	13

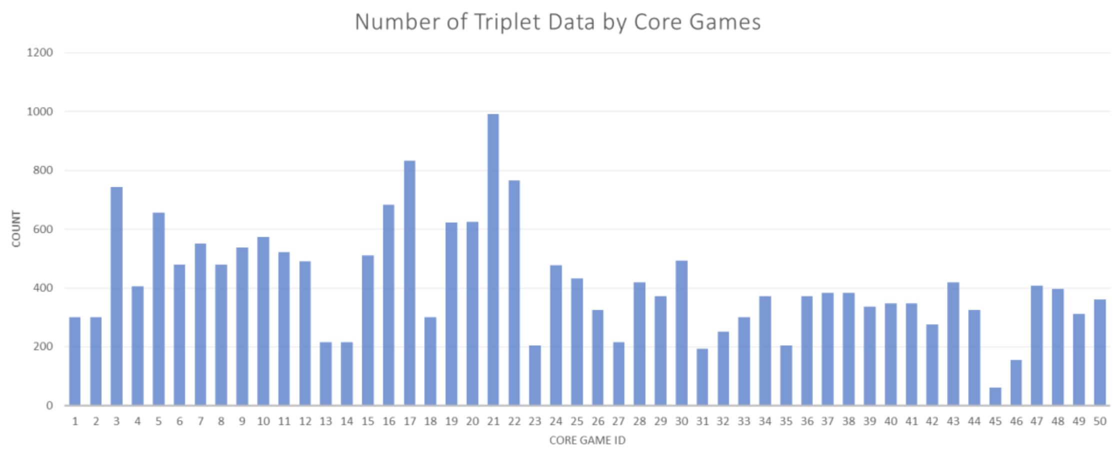
Income	
< 10,000	15
10,000 - 19,999	21
20,000 - 29,999	35
30,000 - 39,999	24
40,000 - 49,999	24
50,000 - 74,999	50
75,000 - 99,999	26
100,000 - 149,999	16
> 150,000	4

Education	
Less than high school degree	2
High school graduate	33
Some college but no degree	58
Associate degree in college	26
Bachelor's degree in college	78
Master's degree	16
Doctoral degree	1
Professional degree	1

D. Triplet distribution

The description and distribution below represent the 6,990 triplets collected in the survey.

Min	60
Max	991
Mean	418.78
Median	384
Std	184.05



E. Core game clusters (experiential genre labels)

The Genre labels for all core games. They are taken as the true labels in the classification model.

Genre 1	Genre 2	Genre 3	Genre 4
Pokemon Red and Blue	The Sims III	Fifa 16	Tekken 2
Mario Party DS	RollerCoaster Tycoon	Mario Kart Wii	Tony Hawk's Pro Skater
Angry Birds	Nintendogs	Wii Play	Civilization V
Guitar Hero III: Legends of Rock	Minecraft	Brain Age: Train Your Brain in Minutes a Day	New Super Mario Bros
Candy Crush Saga	League of Legends	Just Dance 3	Grand Theft Auto V
Clash of Clans	Animal Crossing: New Leaf	Madden NFL 06	Gran Turismo 3: A-Spec
Hearthstone	LittleBigPlanet	Wii Fit	Donkey Kong Country Returns
	Professor Layton and the Curious Village		Splatoon
			Pokemon GO

Genre 5	Genre 6	Genre 7
World of Warcraft	Resident Evil 5	Counter-Strike
Diablo III	StarCraft II: Wings of Liberty	Halo 3
The Legend of Zelda: Ocarina of Time	Warcraft II: Tides of Darkness	Call of Duty: Black Ops
Final Fantasy VIII		Half-Life 2
Need for Speed: Underground		Star Wars: Battlefront
The Elder Scrolls V: Skyrim		
Kingdom Hearts		
Dragon Quest VIII: Journey of the Cursed King		
God of War III		
The Last of Us		
Monster Hunter Freedom Unite		

F. Acquire keywords

I curate a list of "experiential keywords", words considered to be used to express experience. These keywords are identified by searching through *Webster's Unabridged dictionary*'s 105,000-word entries (1913 edition, updated by some transcribers, released and licensed from Project Gutenberg) to identify words whose definitions and example sentences include the seed descriptions. For example, HAPPY can be identified when searching the term, FEELING, since one of the dictionary definitions of HAPPY includes this FEELING word: "feeling pleasure and enjoyment because of your life."

I test a variety of words as the seeds. For example, words describing surroundings, environment, such as SEMBLANCE, MOOD, TONE, FEEL, and IMPRESSION; words that provoke responses, such as ENCOURAGE, MOTIVATE, STIMULATE, EXCITE, ACTUATE, and ENERGIZE; words describing appealing experiences, such as IMMERSE, ENCAPSULATE, CONCERN, CONSUME, ENGROSS, and PREOCCUPY. Filtering away irrelevant results, including EMOTION, FEEL, EXPERIENCE, ENCOUNTER, and SENSATION, a total of 23 seed descriptions are applied in generating the final experiential keyword list, as their results were the most fruitful, containing the best quality of words related to human experiences.

FEEL	AWARE	PERCE	PHYSIC	THOUGHT	SOCIAL
EMOTION	MIND	DISCOVER	MENTAL	CONCEPT	IMAGIN
EXPERIENCE	SENS	VIEW	SPIRITUAL	BELIE	EVENT
ENCOUNTER	STATE	INTEREST	CONCERN	RATIONAL	

Searches based on these 23 seed descriptions provide me with 13,725 words. To make the list complete and with a broad coverage of the universal experiences, I further extend this list by *WordNet*. *WordNet* is a respectable lexicon database curating network relationships between English words. The original list of keywords is expanded with all lemmas belonging to the same Synset and to the hypernym and hyponym Synsets, and with all pertainyms and antonyms of each lemma. This expansion leads to a set of 30,396 words.

G. Experiential keyword samples

400 experiential keywords are randomly chosen and presented.

HUMILIATE	EXECRATE	ABSORB	FUND	DRINK	AVOUCH	ACERBITY	DEED	ECONOMY	POLITENESS
MORTIFY	HATE	ASSIMILATE	BLOT	RECEIVE	DISAVOW	JAUNDICE	ACCOMPLISHMENT	SAVING	CIVILITY
CHAGRIN	DETEST	INGEST	MOP	INVITE	CONCEDE	TARTNESS	ACHIEVEMENT	EMPHASIZING	PROHIBITION
HUMBLE	LOVE	SUCK	BLEND	INTEREST	PROFESS	THORNINESS	AGGRESSION	ACCENTING	INHIBITION
ABASE	ABHORRENCE	IMBIBE	FLUX	BORE	CONFESS	DISAGREEABLENESS	HOSTILITY	ACCENTUATION	FORBIDDANCE
HURT	ABOMINATION	DRAW	MIX	CONSUME	SQUEAL	AGREEABLENESS	ALIENATION	EMPLOYMENT	REFERENCE
WOUND	DETESTATION	EMIT	CONFLATE	INVOLVE	FINK	ACTION	APPLICATION	ENGAGEMENT	CONSULTATION
INJURE	EXECRATION	STEEP	COMMINGLE	ADMIT	SUSTAIN	ACTIVITY	ARRIVAL	FETCH	RESISTANCE
BRUISE	LOATHING	IMMERSE	IMMIX	ACKNOWLEDGE	COMMUNICATE	ACTIVENESS	BEATIFICATION	INTERACTION	OPPOSITION
OFFEND	ODIUM	ENGULF	FUSE	DENY	PASS	INACTION	BRUXISM	JUMPSTART	REVERENCE
SPITE	DISGUST	PLUNGE	COALESCE	RECEIPT	REACT	INACTIVITY	CHANGE	JUMP-START	STUPEFACTION
CRUSH	HATRED	ENGROSS	MELD	NOTICE	RESPOND	INACTIVENESS	CHOICE	KINDNESS	THING
SMASH	PERSON	ENGAGE	COMBINE	RECOGNIZE	MENTION	SUE	SELECTION	BENIGNITY	TRANSFUSION
DEMOLISH	INDIVIDUAL	OCCUPY	MERGE	RECOGNISE	CITE	LITIGATE	OPTION	PERFORMANCE	VAMPIRISM
DEGRADE	SOMEONE	SORB	CONCENTRATE	KNOW	THANK	PROCESS	PICK	EXECUTION	STATE
DISGRACE	SOMEBODY	REABSORB	FOCUS	DECLARE	APPRECIATE	ACCOMPLISH	COURSE	PICKINGS	AGENCY
DEMEAN	MORTAL	RESORB	CENTER	ADJUDGE	ACCEPT	EXECUTE	DESTABILIZATION	TAKING	BEHAVIOR
ABHOR	SOUL	LEARN	CENTRE	HOLD	REJECT	FULFILL	DESTABILISATION	PLAY	BEHAVIOUR
LOATHE	TRANSGRESSION	LARN	PORE	ATTORN	BITTERNESS	FULFIL	STABILIZATION	SWORDPLAY	BUSYNESS
ABOMINATE	EVILDOING	ACQUIRE	RIVET	AVOW	ACRIMONY	ACT	STABILISATION	PLAYING	HUM
ERUPTION	AERATION	DRIFT	SET	SINK	MECHANISM	ACUTE	OBTUSENESS	OPPOSER	REGARD
ERUCTATION	ANTIREDEPOSITION	EFFERVESCENCE	CURING	SOURCE	GUNLOCK	AGUE	SENSITIVITY	RESISTER	FEIGN
EXTRAVASATION	CAPTURE	ELECTROPHORESIS	INACTIVATION	SOAK	MOVEMENT	CHRONIC	SENSITIVENESS	AGONIST	SHAM
OPERATION	CENTRIFUGATION	CATAPHORESIS	ACTIVATION	SOAKAGE	PROCEEDING	INTENSE	SENSIBILITY	DUELER	PRETEND
OVERDRIVE	CHROMATOGRAPHY	DIELECTROLYSIS	IONIZATION	SOAKING	PROCEEDINGS	DISCRIMINATING	INTELLIGENCE	DUELLER	DISSEMBLE
SWING	CONCRETION	IONOPHORESIS	IONISATION	SOFTENING	COUNTERCLAIM	INCISIVE	STUPIDITY	DUELIST	IMPRESS
BATTLE	CONDENSATION	ESTABLISHMENT	LEACH	SORPTION	PROSECUTION	KEEN	DULLNESS	DUELLIST	MOVE
CONFLICT	CONVECTION	ECESIS	LEACHING	STIFFENING	WORK	KNIFELIKE	ADMIRE	ENEMY	STRIKE
FIGHT	CURDLING	EXTINCTION	MAGNETIZATION	RIGIDIFYING	CHALLENGE	PENETRATING	RESPECT	FOE	FEELING
BLOCKADE	CLOTTING	EXTRACTION	MAGNETISATION	RIGIDIFICATION	EXPEDITE	PENETRATIVE	ESTEEM	FOEMAN	ALTER
ENCIRCLEMENT	COAGULATION	FEEDBACK	MATERIALIZATION	STIMULATION	COMPLETE	PIERCING	VALUE	LUDDITE	MODIFY
DEFENSE	DECAY	FILTRATION	MATERIALISATION	SUCCESSION	FINISH	SHARP	PRIZE	WITHSTANDER	HIT
DEFENCE	DEMAGNETIZATION	FLOCCULATION	OPACIFICATION	SURVIVAL	EFFECT	OBTUSE	PRISE	ESTHESIA	HYDROLIZE
EW	DEMAGNETISATION	FLOW	OSCILLATION	SYNERGY	EFFECTUATE	ACUATE	DISRESPECT	AESTHESIA	HYDROLISE
SORTIE	DESORPTION	FORMATION	OXYGENATION	SYNERGISM	CONSUMMATE	NEEDLELIKE	DISESTEEM	INSENSIBILITY	INFLUENCE
SALLY	DIFFUSION	FOSSILIZATION	RADIATION	TRANSDUCTION	DISPATCH	ACCENT	ENVY	CONSCIOUSNESS	TREAT
WAR	DISSOLUTION	FOSSILISATION	RELEASE	TRANSPIRATION	DISCHARGE	ACUTENESS	LOOK	UNCONSCIOUSNESS	QUEER
WARFARE	DISINTEGRATION	HARDENING	SALTATION	VITRIFICATION	DO	ACUITY	ADVERSARY	AFFECT	EXPOSE
ABSORPTION	DISTILLATION	SOLIDIFYING	SCATTERING	PLOT	PERFORM	SHARPNESS	ANTAGONIST	IMPACT	SCUPPER
ACIDIFICATION	DISTILLMENT	SOLIDIFICATION	SERICULTURE	DRIVE	RUN	KEENNESS	OPPONENT	TOUCH	ENDANGER

H. Keyword cluster examples

Group #248, *deity/human hierarchy* experience:

SOUL	REDISCOVERY	SERVITOR	COLONIAL	VINDICATOR	PRINCEDOM	EVERMORE	DISBELIEVER
ENKINDLE	UPHOLDER	YEOMANRY	GOVERNABLE	JUSTIFIER	PROPITIATION	GODLINESS	NONBELIEVER
PROPHESY	SAINTLINESS	DEVOUTLY	INCORRUPT	SHOGUNATE	SANCTIFIED	UNGODLINESS	UNBELIEVER
FORFEND	UNWORTHINESS	SOLDIERY	CIVILIZATION	IMPERIAL	THREESCORE	SORROWING	BOURGEOISIE
KINSFOLK	EVERLASTING	NOBLENESS	FAIN	APOSTLE	DOMINION	EMPEROR	PROVIDENCE
PROVIDENCE	HUMANITY	COLONIZER	EARTHLY	SANCTIFY	SUZERAIN	INCORRUPTIBLE	THENCEFORTH
DOMINION	HUMANKIND	COLONISER	ENLIGHTENMENT	UTTERMOST	EPOCH	MASSES	PSALMIST
PROSELYTE	MANKIND	UNLEARNED	IMPERIUM	APOSTLE	TRINITY	LORDSHIP	DIVINER
COVETOUSNESS	WEAL	ARTICULATOR	WICKEDNESS	CIVILIZED	ASCETIC	PEACEABLE	PROPHETESS
VENERATION	INWARDLY	SHEW	FOUNTAINHEAD	DELIVERANCE	LORDSHIP	AUSPICIOUSNESS	OPPRESSOR
SUPPLICATION	SEER	KINSMAN	GOD	FACTIOUS	LEGATEE	PROPERTIED	UNDEFILED
DIVINE	ILLUMINE	ARIGHT	PROLETARIAT	LEGATE	VASSALAGE	HERETIC	UNBELIEVING
DIVINE	AGAPE	JANISSARY	PELF	ETERNAL	BOURGEOIS	SOJOURNER	SUBALTERN
GODLY	WARLIKE	LEGIONARY	INGATHERING	UNCLEANNESS	DEITY	RESURRECTION	PROLETARIAN
PROVIDENTIAL	SALVATION	POPULACE	SUPERPOWER	RECONCILER	GODDESS	RESURRECTION	PROPHETIC
TRINITY	PREFIGURE	FOUNT	HEGEMON	EVANGEL	SUZERAINTY	FORETELLING	PROPHETICAL
AUGURY	WHEREFORE	PROPHECY	RIGHTEOUSNESS	VIRTUOUSLY	BESTOWER	VOTARY	UNGOVERNABLE
SAINT	REVIVIFICATION	RAIMENT	UNRIGHTEOUSNESS	ASCETICISM	CITIZENRY	MAMMON	ZAMINDARI
FEUDAL	UNBELIEF	FOREMOTHER	EXPIATION	OVERLORDSHIP	ENLIGHTENMENT	SINFULNESS	BROKENNESS
FEUDALISTIC	BARBARIAN	PROPHET	SINGLENESS	SLAVEHOLDING	FAITHLESSNESS	FOMENTER	LANDLORDISM
FEUDALISM	LIBERATOR	MINISTRATION	JINNI	REVOLUTIONIST	KINDRED	BLEST	SONSHIP
OUTCASTE	DIVINING						

Group #206, *mystical* experience:

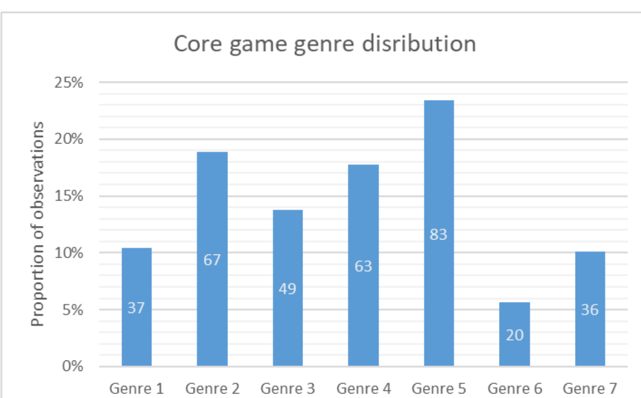
VAMPIRISM	CONNOISSEURSHIP	ABSTRACTIONIST	PORTRAITURE	CABALA	SYMBOLIST	KABBALISTIC	WITCHERY
SPIRITUALISM	DRAFTSMANSHIP	NONOBJECTIVE	CLASSICIST	KABBALA	TRANSUBSTANTIATION	ANIMIST	CONCEPTUALIST
SPIRITISM	ANATOMIST	MIDRASH	THEOSOPHY	KABBALAH	POLYMATH	TANTRA	
MYSTICISM	KABBALIST	DYBBUK	KABBALAH	LANDSCAPIST	ARTIFICER	MYTHIC	
SUPERNATURAL	LOGICIAN	PEDAGOGUE	KABBALA	NECROMANCY	COPYIST	MYTHICAL	
PAGANISM	MYTHOLOGIST	PAGAN	CABALA	AHIMSA	PHRENOLOGIST	MYTHOLOGICAL	
WICCA	ETYMOLOGY	PHRENOLOGY	ANIMISM	LEXICOGRAPHER	SPIRITUALISTIC	LYCANTHROPY	
DEVISER	AFTERLIFE	PHYSIC	MYSTIC	MYSTICAL	KABBALIST	REVISER	

Group #168, *music and dance* experience:

BULL	FUNK	VENTRILOQUISM	RHUMBA	CRUSE	GOSPEL	MIME	
ANIMATED	TECHY	DANCING	RUMBA	BURLESQUE	CROQUET	PANTOMIME	
DICE	RUMMY	MAMBO	SAMBA	RADIOGRAM	PIGSKIN	CREOLE	
SKETCH	ROCK	BOOGIE	MOSH	SHINNY	COCKFIGHT	GLADIATOR	
CARNIVAL	MUSIC	BOP	TANGO	BUNCO	MAYPOLE	DARTBOARD	
CARTOON	BULLFIGHTER	BEBOP	FUNFAIR	BUNKO	PUZZLER	CALYPSO	
DOODLE	CELEBRATOR	CONGA	ALT	PRIZEWINNING	SUDOKU	CALYPSO	
JAZZ	BULL	CONTRADANCE	SANDBOX	LEGGING	CROSSWORD	CREOLE	
FIRESIDE	GOSPEL	DISCO	WITCHING	BUNTING	EIGHTIETH	BLUES	
CANDLELIGHT	CAROL	FOXTROT	DISTAFF	ARCADE	SEVENTIETH	HIGHLIFE	
ANIMATION	PERFECTA	JITTERBUG	BONFIRE	KINETOSCOPE	NATIVITY	CABARET	
ROCK	ORIGAMI	POLKA	CAMPFIRE	SUNDOWNER	BULLRING	TIERCE	
DANCE	PUPPETRY	QUICKSTEP	CRECHE	GRIDIRON	FAIRGROUND	PINBALL	
BLUEGRASS	FISHBOWL	CEILIDH	BULLFIGHT	REVUE	ALT	SOLITAIRE	
SAMPLER	MOD	PHONOGRAPH	RADIOPHONE	ABACUS	SLEIGHING	VAUDEVILLE	
SIESTA	TELEGRAPH	GRAMOPHONE	PANTO	RADIOTELEPHONE	KINETOSCOPE	NICKELODEON	
FOLKTALE	TELEGRAPHY	JUKEBOX	GRIOT	FORMFUL	CORROBOREE	POWDERPUFF	

I. Core game cluster distribution

The distribution of core game genre labels. The unit is one expert review article.



J. Experiential genre word clouds

Below are word clouds generated for Genre #3 to #7, from left to right and top to bottom, by the numerical order of the genre.