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

By

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Abstract

How can subjective experience be effectively portrayed? For experience-intensive products such as video games, product brand, specifications, and other traditional metrics are inadequate in illustrating the delicate and diverse experiences which modern customers seek for. Product genres like first-person shooters, role-playing, and puzzle games may serve as one common and simplistic way to gauge the product experiences. However, they are often overly simplified, unrefined, and thus capture only a superficial form of one's interaction with the product, which is hardly indicative of the rich depth of product experiences one may be exposed to as a player or a customer. Addressing this inadequacy, a new analytical scheme is proposed in this study. This new scheme provides tools that describe product experiences through corresponding product critique reviews. Demonstrated with video game product and its review texts, the scheme employs a classification model to connect true product experiences, retrieved from a survey of real video game players, with product experiential information, extracted via computational content analyses from the review articles. Through this process, this study develops quality measurements 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 the market 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 freight, the RAM[1] size of a laptop to weigh its capacity in completing computational tasks, and the pixel count of a camera to assess its photo quality. With clearly measured criteria of the functional specifications, difficulties are minimized in assessing product performance and competency to the underlying jobs.

Yet, it becomes far harder to evaluate products when their attributes are intangible, unquantifiable, or where some element of subjectivity is involved. Movies, novels, and video games fall into this category—what we call experiential products. In the last decade, increasingly more products shift from providing only physical functions to delivering both physical and mental satisfactions (Brakus, Schmitt, & Zhang, 2007). Businesses incorporate cultural and experiential components 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, a consumption is considered an integral product experience (Khalid & Helander, 2006).

While the product experience is subjectively perceived, we want to assess it objectively in order to evaluate the products connected to it and therefore perform proper judgments and response actions. For the assessment, some practitioners rely on traditional product genres. Such as science-fiction novels and action movies, they loosely capture a general experiential flavor of a product but are mostly superficial,

[1] The random-access memory of a computer system. It is associated with the general processing speed of the system.

barely quantifiable, and therefore unreliable. Other researchers acquire information of experience by interviews and surveys of product users. These interviews and surveys are generally costly because their ways of involving a large number of end users, but, however, rarely effective because the lack of a consensus of what constitutes an experience. Inconsistent items and constructs are used in past research as the instruments of measuring experiences; arbitrary personal scales of the measurements are brought in by survey respondents' individual subjectivity. These add up and produce us only confusing understanding of the product experiences, hindering the evaluation of the experiences to be objective, to be compared across individuals, products, and product categories, and calling for a new method for describing the experiential formation of a product.

Addressing this need, this research proposes a new analytical scheme to describe product experience through product critique reviews—evaluative texts of a particular product, by customers or opinion leaders with expertise in these certain types of products. These product critique reviews, or expert reviews, are more than simply commenting or venting feelings with sentence-long feedbacks; they are usually sponsored by professional product information platforms, such as CNET[2] and MotorTrend[3], and written to express, store, and exchange thoughts and judgments regarding the experts' own experience in a product. Utilizing this natural connection between the text language and human experiences, this research takes the expert reviews as input to identify experience elements and through them portray the product experiences.

In this study, the new scheme is demonstrated with video game and its corresponding review articles, not only because it represents an enormous and growing 91-billion-dollar industry (Takahashi, 2016), but also because it is the kind of product very much emphasizes on providing extraordinary experiences and, therefore, has an abundant of the expert review articles. They are produced to share and

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[2] CNET (http://www.cnet.com) is an American online platform providing information of consumer technology products such as smart phones and laptops.

[3] MotorTrend (http://www.motortrend.com) is an American automobile magazine issued by TEN: The Enthusiast Network. It publishes car guides and reviews in both paper and digital versions.

exchange the video game experiences that is too rich and thus too complicated to be adequately illustrated by a few product specifications or video game genres. 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; there are cultural systems, e.g. in-game society customs and jargon; and there are stories, material resources, virtual currencies, and much more. This virtual ecosphere interacts with players to form the exuberant video game experiences, with which I present this new analytical scheme. It seeks to provide a better understanding of the various human experiences and, with a growing popularity, the multifarious experience-intensive products.

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, 2017). 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 further stressed the meaning of a *state*, including fantasies, feelings, and fun (Holbrook & Hirschman, 1982), which prescribes the experience to be generally unphysical. Among the types of states, *affect* attracts particular attentions, especially in the field of product design, where multiple studies tackled relevant issues (Forlizzi, Disalvo, & Hanington, 2003; Havlena & Holbrook, 1986; Ho & Siu, 2012). The experience with a focus on products, product experience is described as customers' events of interaction with a product (Meyer & Schwager, 2007), the actual participation in the course of the product use, along with the mental states—emotions, feelings, memorable moments, and others—aroused with and responding to the participation.

For video games and other products dominantly emphasizing their product experience, we recognize them as *experiential products* (Cooper-Martin, 1991). Apart from utilitarian ones, the experiential products distinguish themselves by their experiential attributes (Zeithaml, 1988). These attributes are the symbolic, hedonic, and aesthetic natures of a product (Holbrook & Hirschman, 1982)—the features lead to pleasure from product use, such as feeling confident, secured, and exciting by the users (Jordan, 1998). Emphasizing the experiential attributes, experiential products developed distinct characteristics. They stress on a fluent sensory and affective information delivery (Brakus, Schmitt, & Zhang, 2014) and elicit different paths of customer evaluation, which influences product judgment of the customers (Brakus et al., 2007). For the experiential products, customer satisfaction is associated with the entire consumption experience, rather than single attributes or separate consumption stages (Bassi, 2010).

Typical experiential products include films (Bassi, 2010; Cooper-Martin, 1991), music (Lacher, 1989), and video games (Tschang, 2005). In the eyes of some scholars, video games are particularly purely designed experiences (Squire, 2006). During their consumption, they provide little to none physical rewards and, instead, create virtual events to interact with the players. They stimulate players' mental activities, for example, creating a sense of belonging to a virtual warrior guild or weaving friendships during virtual cooperative military operations. In general, the process of playing video games can be deemed as a course of attaining gratification, the positive experiences (Grodal, 2000). These delightful experiences are empirically shown to be associated with players' game preference and amount of time they are willing to invest, a relationship echoes experience's important role in video games as a type of experiential products (Johnson, Gardner, & Sweetser, 2016; Sherry, Greenberg, & Sherry, 2006; Zeigler-Hill & Monica, 2015). In fact, this relationship exists because, through those experiences, players acquire fulfillment of the basic human psychological needs (Ryan & Deci, 2000). It is this satisfaction of needs motivating individuals' continuous consumption in those products (Hassenzahl, 2008), the use of video games and other experiential products.

Traditional ways of Portraying the Experience

While relevant research abundant, our understanding of the product experiences is, surprisingly, limited. Even today, deficiency in the understanding continues because we have not been able to develop a proper approach to evaluate the underlying product experiences. It is the fundamental tool required for any further investigation. I deem the origin of this problem twofold.

First, most, if not all, of the prior studies on product experiences used questionnaires and interviews as their primary source of data (e.g. Oswald, Prorock, & Murphy, 2014; Poels, de Kort, & Ijsselsteijn, 2012; Quick, Atkinson, & Lin, 2012). In traditional surveys, questions and answer options are limited by researchers' decisions. At the meantime, the responses are subject to individual scales of the survey respondents. These constraints do harm to research objectivity, especially when the underlying experience is so subjective and intangible that no overarching theory to govern the questions to be asked and the measure scales to be employed. No one can possibly be certain that when I say, "I have a strong feeling of companion," where the "strong" is the same "strong" when you are making the same argument.

In addition, more open-ended questions suffer from a strong but often unmet prerequisite that the surveyed customers have to know well the underlying experience and possibly the theoretical constructs behind. There would always be survey subjects asking, "does this feeling count as an experience?" or "what kinds of emotion did I really have?" "A lot of times, people don't know what they want until you show it to them" (Steve Jobs, recorded by Mui, 2011). To survey respondents, the answers researchers seek for are just like the inexplicit needs described by Jobs, they are often tacit and cannot easily be recognized by ordinary customers, even by researchers without specific training and sufficient cognitive processing. The surveyed individuals' incapability of properly responding to the questions can impair the analyses based on their answers.

Second, in the past research, product experiences are primarily measured based on certain rough categories, such as the traditional genres where a video game belongs (e.g. Billieux et al., 2013; Fuster et al., 2014; Gao et al., 2013; Kim & Ross, 2006) or the platforms where a video game publishes (e.g.

Klimmt, Schmid, & Orthmann, 2009; Mccauley, 2014). These unrefined genres and measurements oftentimes do not describe well the experiences consumers can have with a product. For example, both first-person shooter games, *Counter Strike*[4] stresses on team cooperation while *Half-life*[5] provides strong story-telling elements. This difference leads distinct in-game experiences of the two games despite they have the same traditional video game genre. This discrepancy between video game experiences and the traditional genres was empirically demonstrated in the literature. Park, Song, and Teng (2011) build a model based on players' personality that effectively predicts players' penchant for the types of gaming experiences, while, on the contrary, they could not find connections between the personality and the player's preference in the traditional video game genres.

An alternative to these current experience measurements and approaches is what this research attempts to deliver—an objective framework to assess the product experiences. This research first identifies human experience elements based on the English lexicon and, through these elements, extract experience of specific products from expert product review texts via techniques of content analysis. It utilizes a natural connection between the language and human experiences as a new approach in portraying, or measuring, 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 interact with human cognition, influence how people see and act toward themselves, things, individuals, and the society (Carley, 1994; Levi-Strauss, 1976). These cognitions and

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[4] A first-person shooter multi-player game in which players are divided into terrorist and counter-terrorist groups. With goals corresponding to a group's role, players cooperate with members of the same group and combat against the opposite group, performing tasks like capturing hostages or dismantling a bomb.

[5] A first-person shooter single-player game features immersive control, solving puzzles when interacting with the game environment, and a suspenseful storyline of investigating an alien research facility.

interactions of individuals with the environments, they are also the human experiences, stored, exchanged, and construed with the use of languages (Halliday, Matthiessen, & Yang, 1999).

From the languages, tangible human behaviors and the social facts can be observed (Saussure, 1959). For example, adoption of a technology (Michel, 2011) or the interaction between individuals (Kossinets & Watts, 2014). Moreover, this observation can 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 can be examined. Therefore, 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) from a corpus of academic journals (Shi, Foster, & Evans, 2015) or a compilation of news articles (Semetko & Valkenburg, 2000); at a micro level, they identify individual opinions (Pang & Lee, 2008) from online posts for a stance in a debate (Fermín L. Cruz, Troyano, Ortega, & Enriquez, 2011) or customer comments for an opinion toward a product feature (Tian, Xu, Li, & Pasi, 2014; H. Zhang, Sekhari, Ouzrout, & Bouras, 2016).

From languages and the communication artifacts built upon, the human experiences are ready to be examined with proper approaches. Among them, one common method is the 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; Kim & Hovy, 2004; Yi, Nasukawa, Bunescu, & Niblack, 2003). From the meaning of each single words and of higher level linguistic patterns shown in the texts, this method evaluates semantic closeness of the sentiment concepts and the research topics, for example, how much a writer likes or dislikes a product (Jadi, Claveau, & Daille, 2016).

When doing sentiment analyses, researchers often curate concept-specific lexicons, for example, a collection of words expressing positive sentiments and another of words representing negative ones (Das & Chen, 2007; Hurst & Nigam, 2004; Taboada, Brooke, Tofiloski, Voll, & Stede, 2011; Yi et al., 2003). Through the lexicons, researchers locate the target words and observe their patterns and interactions with linguistic contexts of the document for understanding the focused sentiments. Similarly, this study curates a lexicon of experience, which contains potential English words connected to the human experiences. These experiential keywords are identified via inversed searches in accredited dictionaries (Bolukbasi, Chang, Zou, Saligrama, & Kalai, 2016). This method is further elaborated in the Data section.

Advanced sentiment analyses observe more complex concepts, such as affects (Cambria, 2016) and product consumption experiences (Xiang, Schwartz, Gerdes, & Uysal, 2015). They deal with longer and more sophisticated texts and apply refined computational methods to address large volumes of input and complex linguistic structures, coming along with the length of the text, for example, the product expert reviews.

In this research, I employ the product expert reviews curated by major product information websites with the sentiment analyses for the exploration of product experiences. Compared to short comments or ordinary customer feedbacks, the product expert reviews provide more than positive/negative evaluations of a product—they help convey product experiences to its readers by relaying the various experiential dimensions in the texts. Concerning the video games, they speak of the kinds of in-game systems a game has, the various challenges players will encounter, the storylines, and the various intricacies of a video game's social world. They are more objective, because the product information websites rely on the objectivity and the texts' loyalty in communicating true experiences to attract viewers. The expert reviews are often with a better quality of delivery, because they are written by professional writers, who wield languages better and write particularly when the experiences occur.

Data and Method

I present ways of acquiring experience descriptions by harnessing ideas of the advanced sentiment analysis in extrapolating product experiential genres and features from expert review texts. In this research, efficacy of these experience descriptions is further attested via an operative classification model, demonstrated with video game products and a corresponding review corpus. To start with, real experiential genres of a selection of video games are identified as response variable of the classification model through a survey of real video game players. Meanwhile, experience features of each of the selected games are addressed in the expert review texts as the predictor variables by a sequence of computational content analysis. Finally, these experience features are applied with four different classifiers to predict the real experiential genres of the selected games. Successful prediction of the experiential genres evinces the connection between them and the review texts. This vouches for the effectiveness of the experience features and genres identified from the review texts in describing the real product experiences revealed in the survey.

Response Variable - Experiential Genre

Experiential genres are game categories premised upon experience from playing video games. Identifying those genres, a survey[6] is conducted with a small subset of video games through Amazon Mechanical Turk (MTurk)[7] targeting experienced video game players[8]. The games used in this survey are selected 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 shooters[9] and role-playing games[10]. These criteria are applied in an attempt to achieve the best possible representativeness and diversity of the video game experiences. In addition, the number of games to be included is intentionally limited to ensure a sufficient number of response can be collected representing each of the games. As a

[6] The survey was designed through Qualtrics and conducted in April, 2017.

[7] Owned by Amazon, an online crowdsourcing platform for human intelligence tasks, tasks require human judgments such as social sciences experiments and surveys.

[8] Survey subjects must pass a preliminary test to be able to participate in the major part of the survey. The test includes five questions about content of specific video games a subject claims that he/she is familiar with. The subjects must have a correct rate higher than 80% to pass the test.

[9] A video game genre its gameplay emphasizes a first-person angle of view, often combined with gun-based combat systems. In the games, players experience combats through the eyes of the protagonists.

[10] A video game genre its gameplay allows players to play the roles of in-game characters. Players experience the events unfolding around the characters, controlling their actions and reactions, and making decisions on behalf of them.

result, fifty video games are chosen as "core games" to be presented in the survey and subsequent analyses, 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*[11].

With 350 participants[12], the survey collects 6,990 experiential resemblances in a triplet form—the relative similarity of game A to B and to C[13]. It is a form intentionally simplifies the structure of questions to decrease cognitive burden of the respondents. Lower cognitive loads result in more precise self-report results, not disturbed by the questions themselves and the respondents' knowledge of experience.

These triplet-resemblances are built into a high-dimensional space via the t-Distributed Stochastic Triplet Embedding (t-STE; Van Der Maaten & Weinberger, 2012), where distances between each game preserve the similarity of the games' experiences[14]. 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 this specific triplet data form (Van Der Maaten & Weinberger, 2012).

Through the t-STE, twenty-five dimensions are extracted 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[15]. Like other dimensionality reduction techniques, the goal of the t-STE algorithm is to define a subset of possible dimensions to extract as much of the consistently meaningful information, the information helps the correct description of the relationships between the objects. In Figure 1, the model error rate gradually reduces until sticking around 18%, when the number of deminsions achieve and go over twenty-five. With more dimensions extracted, more information is preserved at a cost of including

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

[12] Demographic description of the survey participants and the triplet distribution is provided in Appendices C and D, respectively.

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

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

[15] 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.*

more random noise. When additional dimensions provide trivial or none improvement of the power of explanation, the dimensions added are assumed to capture only unwanted noise. As the error rate do not reduce substantially after the first twenty-five dimensions, the twenty-five version of the t-STE scores is, therefore, selected to be applied in the subsequent analyses.

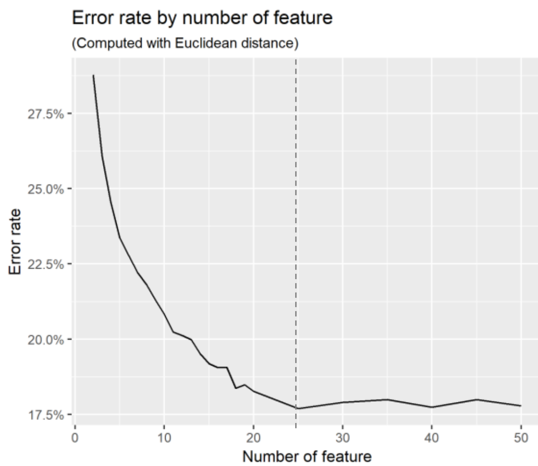

Figure 1. t-STE Error Rate by Number of Features

With the twenty-five dimensions, I conducted a hierarchical clustering via the Ward variance minimization algorithm (Ward Jr., 1963) to group the core games into several game experiential genres. Instead of non-hierarchical methods such as the k-means, the hierarchical one is implemented to better fit a potential nested structure of the human experiences. For example, an experience of war could consist of the images of battlefields, weapons, and casualties, while the image of casualties could further be related to the concept of blood, wound, or death.

The hierarchical clustering starts with each core game as its own cluster, and each time merges a pair of clusters based on a target of minimizing the total within-cluster variance after the merge. To determine a proper number of clusters, the elbow method is employed. In Figure 2, the distance equals to the increase of total within-cluster variance when a merge is performed (the number of clusters is decreased). The blue line stands for the distance growth between each merge; the orange line presents the distance growth acceleration, the first order derivatives of the distance growth. As a large distance increase is assumed to reflect the natural or true group boundaries, the ideal number of cluster is, therefore, suggested to be the peak growth acceleration at two, then five, and seven. Considering also the meaningfulness of the formation of the acquired cluster membership, the seven clusters were selected[16] to represent the seven experiential genres in the latter part of this research.

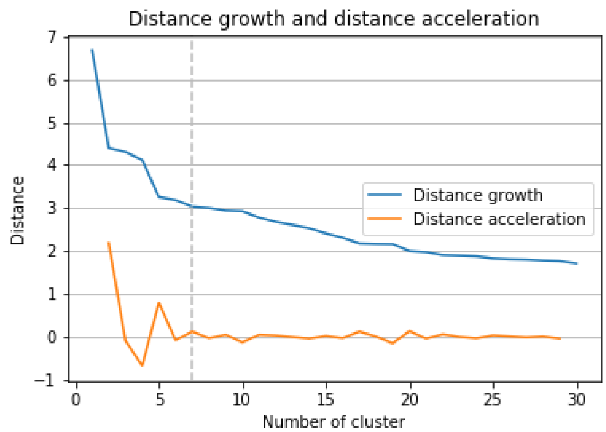

Figure 2. Distance Growth and Distance Acceleration of Clustering Merges

The clusters are then 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 a satisfactory quality of the clusters, each characterizes a distinct emphasis on the experiences.

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

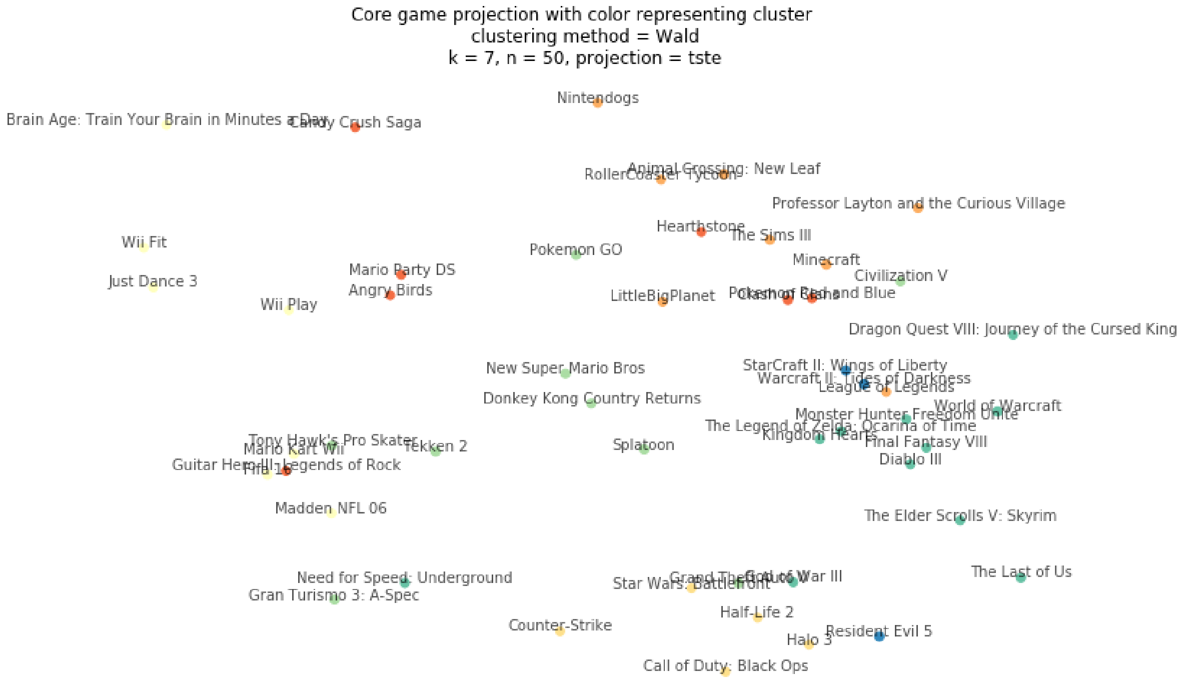

Figure 3. Core Game Projection with Cluster Labeling

For example, Genre #2 (the orange genre) includes traditional simulation games[17], as well as several multiplayer online battle arena (MOBA)[18] and puzzle games[19], expressing a creation, or creative, experience of the games. This genre includes eight core games listed in Table 1. *Nintendogs*, *RollerCoaster Tycoon*, and *The Sims III* are the traditional simulation games. For example, *RollerCoaster Tycoon* provides a context for the players to manage a virtual theme park, where players decide what rides to be introduced in the park and, with them, how to attract customers to make more profit to further develop this theme park. The simulation feature of the games provides great freedom and, intuitively, requires the players to be creative to succeed in those games. Interestingly, four other games of this

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[17] A video game genre its gameplay aims at simulating real world events and activities. A player could emulate managing a company, administering a city, or even living through another person's life, via the virtual worlds and opportunities to make decisions provided by this type of game.

[18] A video game genre its gameplay requires players perform real-time strategy, combatting other players in a closed environment (the arena). During a combat, one player controls an army. It is often led by a hero, who can be trained and grown, be equipped, and be commanded to interact with game environment and armies controlled by other players.

[19] A video game genre its gameplay features puzzle solving activities. Common types of puzzles include pattern recognition, logical deduction, timing of actions, etc.

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[20], *Minecraft* is a sandbox[21], *League of Legends* is a MOBA type game, and *LittleBigPlanet* is a platformer[22]. 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 (Reparaz, 2008). 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 creatively form a team of five, each operate a champion and cooperate with others. Simply consider the number of combinations of champion selection by five players in a team, each with 136 possibilities: it is 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 published in the last three decades, from 1995 to 2017. Games represented by the reviews are across platforms, traditional game genres, and developers and publishers to be representative.

[20] A video game genre its gameplay has the characteristics of both puzzles games and adventure games.

[21] A video game genre its gameplay emphasizes a greater freedom of the players. This type of game often does not provide explicit winning goals to the players. Instead, it acts as a platform which provides diverse materials, tools, and mechanics and encourages players building stuffs from scratch, creating new ways of interaction with the game environment.

[22] A video game genre its gameplay is primarily delivered with players controlling protagonists jumping between platforms. This type of game requires players' reaction to the game environment, or the platforms, with good hand-eye coordination.

Each review contains an average of 1,170 words, which amasses a total of fifteen-million words of analysis.

Furthermore, the review collection corresponding to the fifty core games is specifically expanded to include game reviews of additional information websites, such as IGN, GameFAQs, and PC Gamer, to ensure a satisfactory size of review samples to be used in the models. The compilation of core game reviews then contains a total of 355 review articles. Each review article makes up one individual observation in the subsequent model training process.

For the entire review corpus, stopwords[23] are removed using the Natural Language Toolkit (NLTK)[24] English stopword dictionary; no stemmers[25] and lemmatizers[26] are used as to preserve information of sentence structures, a critical input to the text processing algorithm applied in this research. A word cloud is provided in Figure 4, showing high-frequency terms of the filtered 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.

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[23] Words do not contain significant meaning, for example, THE, A, and OF in English. Stopwords are often filtered out before performing natural language processing tasks (http://i.stanford.edu/~ullman/mmds/ch1.pdf).

[24] NLTK is a primary resource platform providing various supports in human language analysis for Python programs, including APIs, modules, and assorted lexical resources.

[25] A human language processing tool performing stemming to the words to be analyzed. The tool translates the words into their root forms by stripping grammar-purpose suffixes such as -S, -ED, and -LY. This process could improve performance of certain types of natural language processing tasks (Baeza-Yates, Ricardo; and Ribeiro-Neto, Berthier (1999); Modern Information Retrieval, ACM Press/Addison Wesley).

[26] An advanced stemmer tool which takes into consider words' part-of-speech information (e.g. a subject or a verb) when doing stemming tasks.

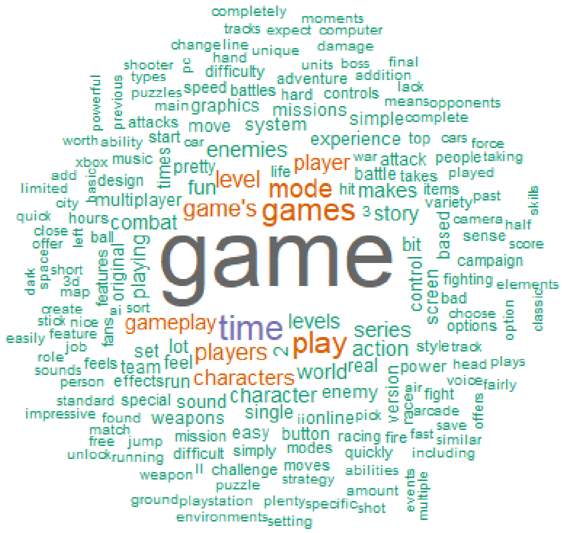


Figure 4. Game Cloud – Video Game Corpus

The corpus is then applied with the Word2Vec (W2V; Mikolov, Sutskever, Chen, Corrado, & Dean, 2013) negative sampling to provide a 300-dimensional space, where words contained in the corpus are embedded according to the context of usage and expressed via word vectors. While words frequently used in a similar circumstance in the texts are represented close to each other, this embedding captures semantic similarities between the words of the corpus 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; Le & Mikolov, 2014) 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 the idea of the sentiment analysis and operates a document's cosine similarity, in the W2V space, to each "experience concept group" as the feature.

In W2V space, a document vector is a conceptual centroid of all word vectors belonging to the words constitute this specific document text, and, therefore, represents an average semantic orientation of this article. As expert reviews are a linguistic concretization of experience playing the corresponding video games, their document vectors are deemed as the integrative experience features of those games.

The benefit of employing this document vector approach is twofold. First, the document vectors are efficient to acquire through the D2V algorithm considering the required computer processing facility. Second, this approach has been verified repeatedly in previous studies to be effective in summarizing semantic orientation of an article. However, one major drawback of the D2V approach is that the experience features obtained from it are arbitrary and by themselves cannot be explained meaningfully because dimensions of a W2V space are themselves arbitrary and cannot be easily expounded.

On the other hand, the concept groups are clusters of 30,396 experience keywords, words considered to be used to express experiences. These keywords are identified by searching through *Webster's Unabridged dictionary*'s 105,000-word entries (Porter, 1913; updated by some transcribers, released and licensed from Project Gutenberg) to obtain words whose definitions and example sentences include certain seed descriptions[27] (Bolukbasi et al., 2016). For example, HAPPY can be identified when searching the term, FEELING, since one of the dictionary definitions of HAPPY includes the FEELING term: "feeling pleasure and enjoyment because of your life."

To make the experience keywords with a broad coverage of the universal experiences, I further extend this list by *WordNet* (Fellbaum, 1998). It is a respectable lexicon database curating network relationships between English words (Agarwal & Bhattacharyya, 2005; Ohana & Tierney, 2009). To ensure the curated lexicons complete, expansions by *WordNet* are common, proved useful (F. L. Cruz, Troyano, Ortega, & Enriquez, 2011; Verma & Pushpak Bhattacharyya, 2009), and often seen applied in sentiment analyses. (Andreevskaia & Bergler, 2006; Poria et al., 2012). The original keywords are first expanded with all lemmas[28] which belongs to the same *WordNet* synsets[29], and then added with the

[27] The process of identifying the seed descriptions is described in Appendix F in further detail.

[28] The root words acquired by lemmatizing the original words.

[29] Synonym set of a word. For full definition, refer to: https://wordnet.princeton.edu/wordnet/man/wngloss.7WN.html.

keywords' hypernyms[30], hyponyms[31], pertainyms[32], and antonyms, leading to a set of 30,396 words.

Some randomly selected sample keywords are shown in Table 2[33].

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 keywords are clustered with the Ward algorithm into 10, 30, 100, 300, and 1000 concept groups, by their semantic meaning revealed in the Google News W2V space[34]. The produced keyword clusters are considered the "experiential concept groups" as they each gather 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 the other hand, Group #11 contains a particular experience of the military (

[30] "Y is a hypernym of X if X is a (kind of) Y" (Princeton University, 2010). For full definition, refer to the above webpage.

[31] "X is a hyponym of Y if X is a (kind of) Y" (Princeton University, 2010). For full definition, refer to the above webpage.

[32] Related adjectives. For full definition, refer to the above webpage.

[33] More examples in Appendix G.

[34] 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.

Table 4), as the keywords include not only types of armed forces but also actions, equipment, and facilities commonly associated with the troops[35].

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	

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

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		

Regarding the second approach, a game's experience features are defined by its review document's cosine similarity to each "experience concept group" in the W2V space. One major advantage of this approach is explicability of the features. While the features are derived from the experiential concept groups, one can easily trace back to original experiential keywords consisting of the concept group and uses the meaning of these words to define this specific feature. However, distance calculation for the features can be computationally expensive when the experiential keywords are many.

Classification Model

With multiple classification models, I extract experience features from the 355 review articles, corresponding to the fifty core games, in predicting the games' real experiential genres, which are identified in the survey. Both approaches of acquiring the experience features—using the Doc2Vec and using the documents' distances to the experience concept groups[36]—are applied. This current study attempts four different classifiers to identify the best-fit method: Support Vector Machine (SVM, with the linear kernel), Neural Nets (Multi-Layer Perceptron (MLP), with 100 hidden layers), Random Forest, and Multinomial Naïve Bayes, because the unknown nature of human experiences.

These classification models are trained, and the error rates, the probability the models predict the games' experiential genre into a false one, are reported and reviewed under a cross validation to confirm the connection between these two constructs, the experiential genres and the expert review texts. One step

[36] Including 10, 30, 100, 300, and 1000 versions of experience concept groups, their corresponding distances to the document vectors.

further, the best classification model is applied to other games not included in the original survey to obtain the predicted experiential genres. These predicted genres are thereafter examined to once again confirm the established connection and to identify experience features best distinguishing, or portraying, the underlying genres.

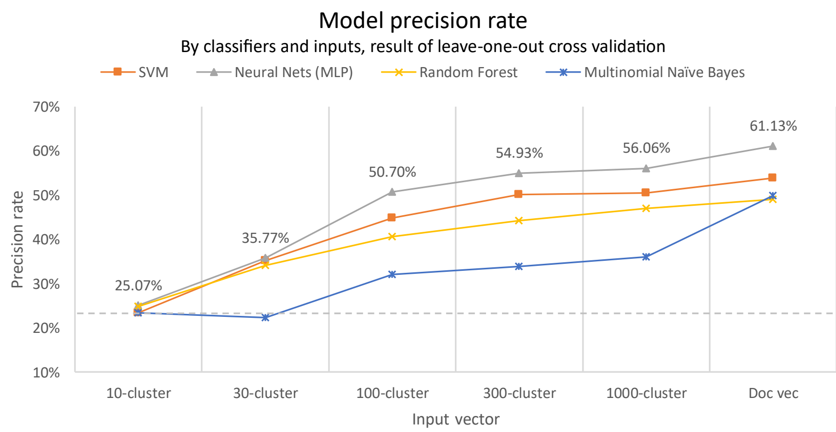
Result

Training and Validation

All combinations of the classifiers and the input features are applied in the model training process. The model precision rates are taken as the evaluation standard of model performance under the leave-one-out cross validation, which ensures a quality measurement of performance by preventing researchers misguided by over-fit models. They falsely include noise information when fitting data and therefore funtion well with the same training data set but poorly when applied to a different testing set of data. The cross-validated performance summary is provided in Table 5 and Table 5.

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%	61.13%
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%



Among all models, the Neural Nets performs the best while the Multinomial Naïve Bayes does the worst. This is probably because a hardly held strong assumption required by the Multinomial Naïve

Bayes models. The Naïve Bayes classifier demands features of a model statistically independent of each other. However, in the context of the human experiences, the experience features, or the elements of an experience, are naturally interwoven with each other and cannot be easily dissected into unrelated pieces. On the other hand, the Neural Nets classifier is more relaxed to assumptions. It also applies the most complexed computing procedures to extracts the most details out of the data.

With document vectors as input, the Neural Nets model tops a 61.13% precision rate in predicting the correct experiential label out of seven, a substantial improvement from the baseline of 23.38%[37]. This huge improvement of the precision rate confirms the existence of 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 each specific genre, the models function well in almost all except Genre #6. In Figure 6, numbers in the cells show the case count of each true and predicted label combination. The diagonal cells represent the cases whose predicted labels identical to the true labels, the cases of correct prediction. The deeper the color, the more the cases fall into that label combination. In the figures, the colors are dark of all diagonal cells except for the true label #6. This characteristic is observed in generally all model variations[38]. One possible reason is a relative underrepresentation of Genre #6. The Genre #6 cases constitute only 5.63% of the 355-review-article sample, compared to 23.38% of the largest genre. The smaller sample size may lead to insufficient experience information identified during the model training process for a robust classification. Including more sample articles representing this specific genre is expected to be helpful in better prediction performance.

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

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

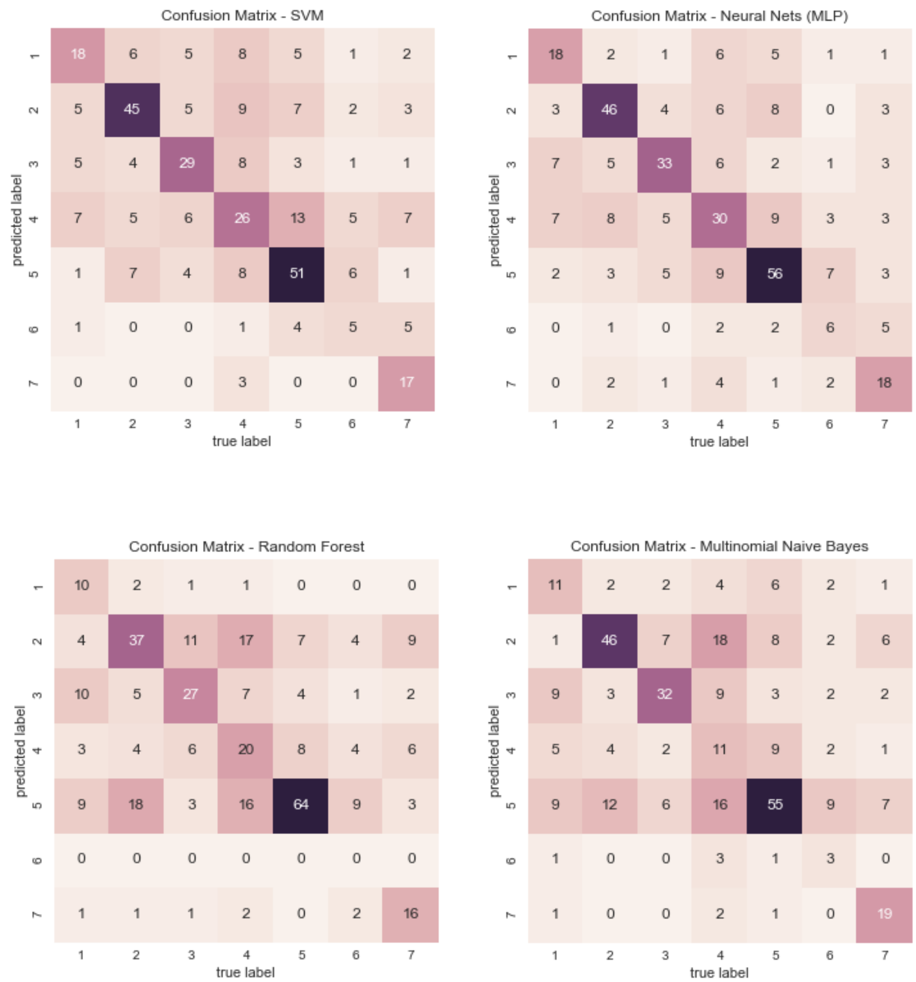


Figure 6. Confusion Matrices - Document Vectors as the Input

On the other hand, model precision rate increases when more features are included in the model. Regarding the experiential concept groups, the 10-cluster models produce a result only close to the baseline. From 30, 100, and up to 1000 clusters, precision rates rise across all classifiers when more clusters were employed. However, the marginal increase diminishes drastically after the 100-cluster input; the precision rate can be improved approximately only 5% with ten 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 of the W2V document vector features.

However, one must note that, the model is built upon a limited fifty core games and their three hundred review articles. Despite the cross-validation, it would be helpful to apply the same method, the survey, information extraction, and the classification model, to a different set of games and benchmark the new performance for a stronger confidence in this construct. Moreover, generally in this context, performance differences between models are quite thin (generally less than 10%). Consequently, between computational complexity and the model precision rate, the exchange should always be left to researchers' discretion regarding the goals of their analyses.

Prediction of Non-Core Games

This best-fit model is applied to the rest of 15,727 game reviews in the expert review corpus and estimates experiential genres for the eleven-thousand non-core games. The results are projected with the t-Distributed Stochastic Neighbor Embedding (t-SNE) and shown in Figure 7 with some popular games randomly selected to be marked on the map.

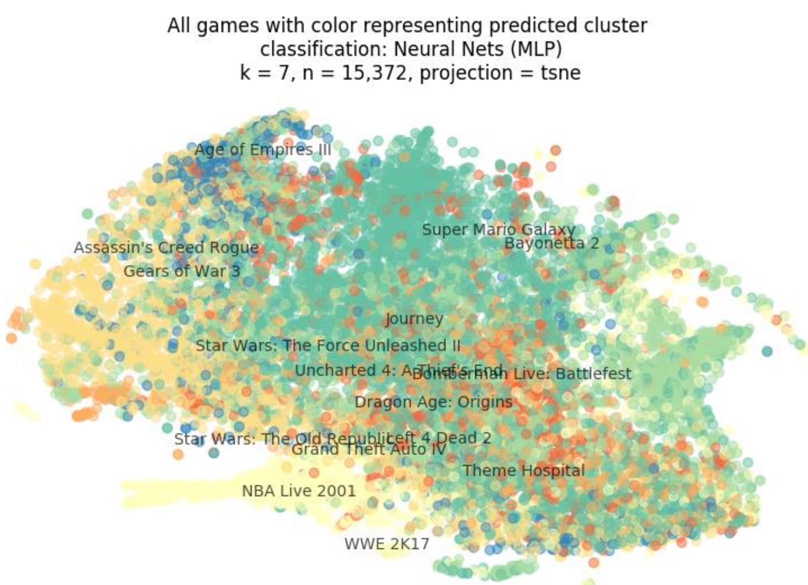


Figure 7. Non-Core Games Projection - Document Vectors as the Input

In general, the result is promising—the selected games are distributed conforming to their in-game experience types. 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.

The projection also demonstrates the capability of the underlying model capturing the between-genre variation as shown by the distribution of the colors. This 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.

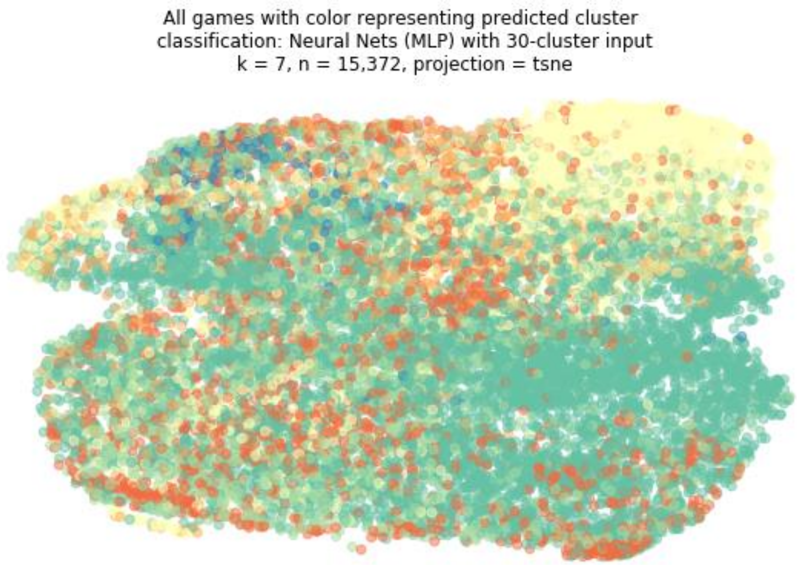


Figure 8. Non-Core Games Projection - 30-Cluster as the Input

Portrait of the Experience

With a 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)[39].

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

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

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, represented 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[40], Genre #2 has the lowest score, among all genres, on Concept Group #11, a concept group denoting the *military force* experiences and comprises of keywords such as SUBMARINE, MISSILE, and BATTALION. Consistent with our previous observations on Genre #2, these keywords properly signify the opposite experiential nature of the genre's member titles such as the *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[41], 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*.

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

[41] The exemplified concept groups and the element keywords of each group are provided in Table 3,

Table 4, and Appendix G.

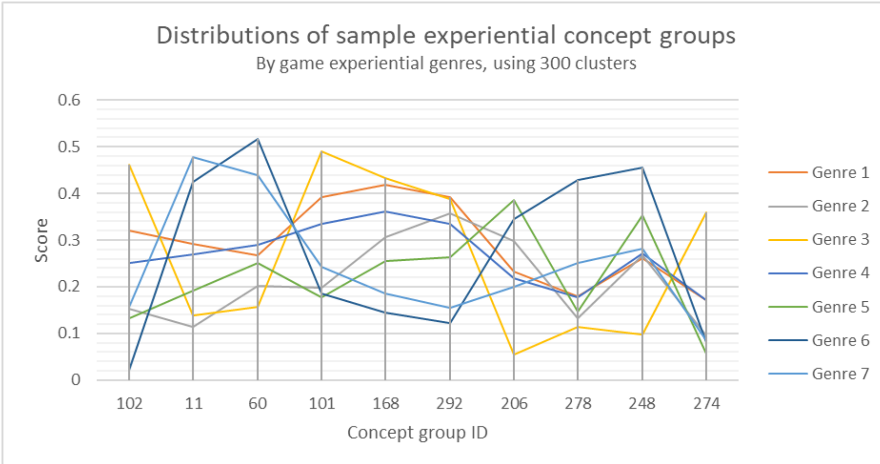

Figure 11. Distributions of Sample Experiential Concept Groups

Discussion

Limitation and Future Direction

Several refinements could be considered in future studies. First, expanding the sampling inputs would make our model much more robust. For example, augmenting the core game set beyond fifty 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. Therefore, we would expect the model's predictive ability improved by including more than one article per game, as more reviews of diverse sources cover more and different features of a game. This better coverage improves not only available experience information of a game but also comprehensiveness of the entire corpus.

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 mismatched ones. I 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 my attention in trying to describe elements of a process of “experiencing”. In other words, this was still a rather arbitrary process, and I believe that it can be improved if using a more linguistically sound procedure that yield 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 could have to be counteracted by a larger sample size. On the other hand, concerning the classification model itself, we might also be able to improve its performance by modifying the underlying Neural Nets classifier with algorithms more sophisticated than the simple MLP structure.

Conclusion

As a natural progression of a society, the rising importance of experience is a necessity to developed economies (Pine & Gilmore, 1998). The growing markets of delicate tours, customized online education, and personalized health care services are just a few examples; experiential products like movies, novels, and video games are especially gaining popularity in our society. These products focus specifically on experiences and deliver mostly their values through the well-designed experiences. For a better understanding of these products and the abundant and profound experiences with them, this study proposes a new analytical scheme of product experiences, utilizing the texts of product expert review and natural language processing instruments.

This scheme is demonstrated with the video game product and its corresponding review corpus. With this scheme, I first validate the effectiveness of employing the review text in portraying the experiences. In a 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 over 60% compared to the baseline at 23%. The relationship between these 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 model and its application expands our toolset in understanding product experiences with the expert review texts.

Portraying the product experiences, this research develops quality measurements. As subjective judgments from the end-users are largely reduced, the new measures are easily quantifiable and relatively objective compared to the traditional ones. For the starter, seven potential game experiential genres are identified through the triplet comparisons, which simplify the involvement of the participants and help to reduce fatigue of 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 addition, from a semantic construct of the language, I propose a new process in identifying human experience elements. Including the experiential keywords and their concept groups, they leverage the nature of human language development and explore the linguistic structure for a different approach in delineating product experiences. These new experience features are more than ordinal items used in traditional surveys. They can be easily measured and compared across individuals and products.

Moreover, also because less direct involvement of the end-users, this analytical scheme describes product experiences in a much economical way. The full-scale application of the classification model illustrates the in-game experiences of more than eleven-thousand video games with only the review texts as the input, which can be easily and cost-effectively obtained from the web, in contrast with conducting real player surveys and, along with it, all the financial expenses and logistics problems caused to be able to cover the eleven-thousand video game titles.

Lastly, while demonstrated with video game products, this scheme is ready to be generalized and applied to other experiential products. Our methods of identifying experiential keywords, doing triplet surveys and embedding, and tagging the game titles by their review texts can be easily replicated with other consumer products also heavily experience-based. Movies is an excellent example. Beside the stories, acting, and post-production effects, more filmmakers today are investing in the 3D and even 4D technology to pander to the five senses of the audience. 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, blogs, and professional critiques. They are the best materials and can easily be applied with the scheme to acquire an understanding of the filmed experiences from a whole new angle.

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Technical Appendix

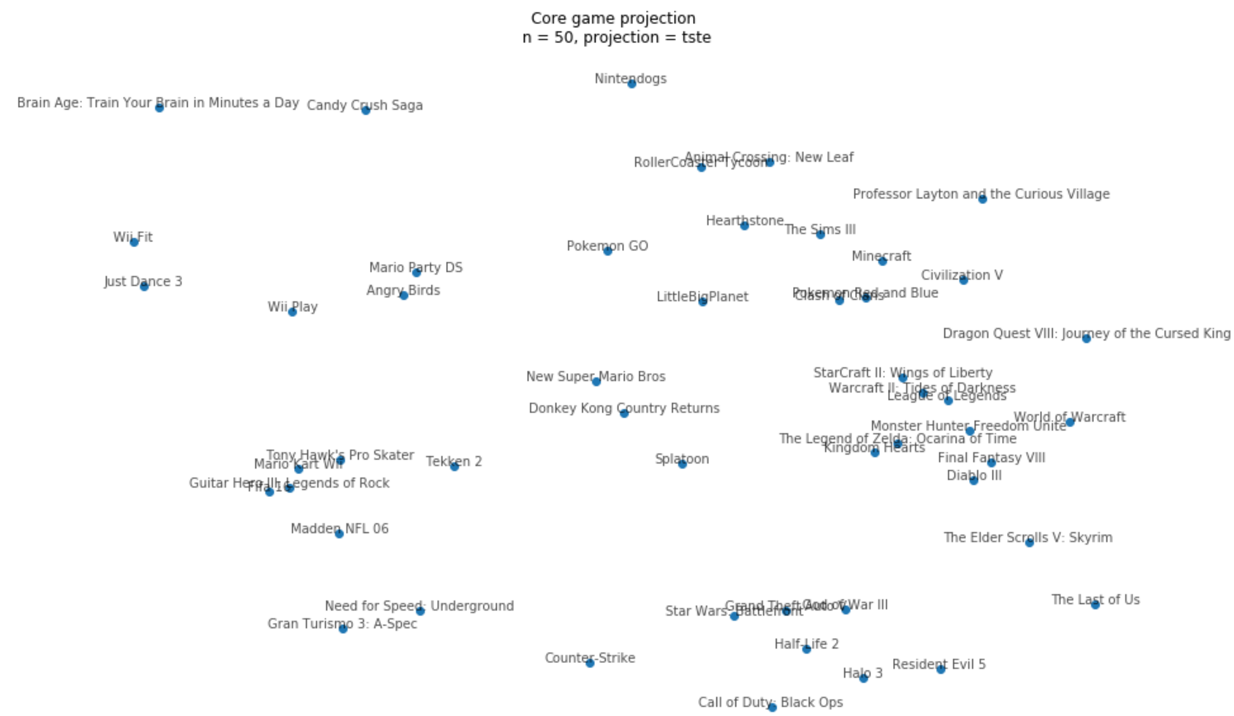
A. Core game list

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

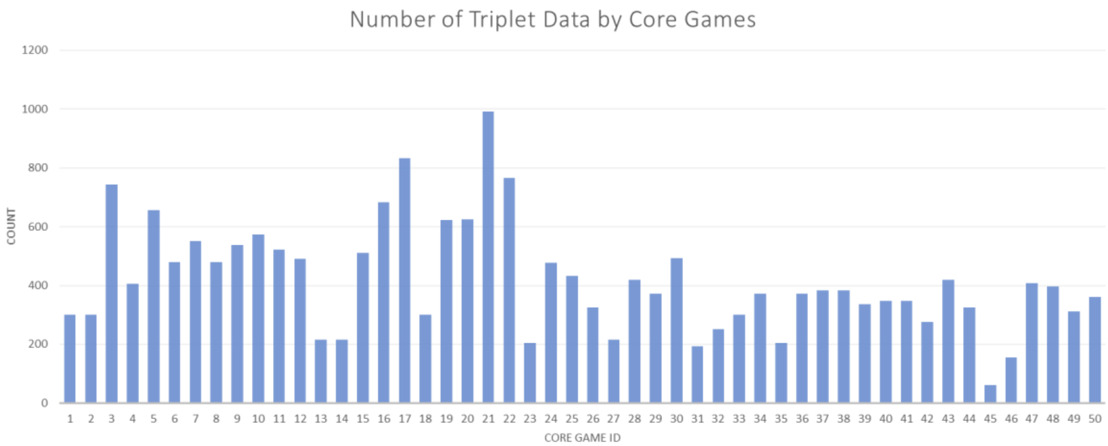
Income	
< 10,000	15
10,000 - 19,999	21
20,000 - 29,999	35
30,000 - 39,999	24
40,000 - 49,999	24
50,000 - 74,999	50
75,000 - 99,999	26
100,000 - 149,999	16
> 150,000	4

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. Keyword reverse search seeds

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

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. Searches based on these 23 seed descriptions provide me with the original keyword bank of 13,725 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:

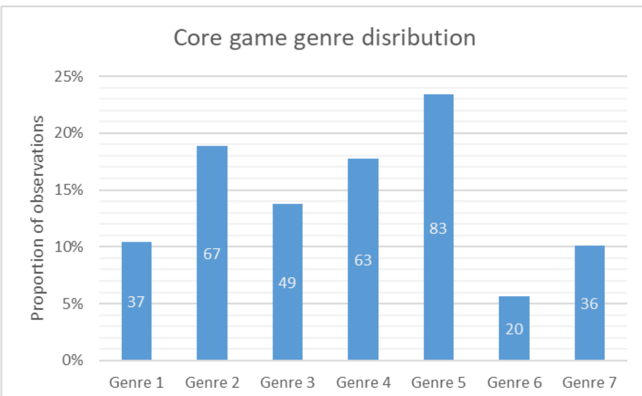
VAMPIRISM	CONNOISSEURSHIP	ABSTRACTIONIST	PORTRAITURE	CABALA	SYMBOLIST	KABBALISTIC	WITCHERY
SPIRITUALISM	DRAFTSMANSHIP	NONOBJECTIVE	CLASSICIST	KABBALA	TRANSUBSTANTIATION	ANIMIST	CONCEPTUALIST
SPIRITISM	ANATOMIST	MIDRASH	THEOSOPHY	KABBALAH	POLYMATH	TANTRA	
MYSTICISM	KABBALIST	DYBBUK	KABBALAH	LANDSCAPIST	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.