Method and Result:

Portray Video Game Experience by Expert Reviews—
Potential Experiential Genres and Classification Models

Course Project of MACS 30200

Chih-Yu Chiang

Contents

I. Identify Game Experiential Genres from Survey ... 4
1) Core Game Selection ... 4
2) Triplet Survey on In-game Experience ... 4
3) In-game Experience Triplet Embedding ... 5
4) Core Game Clustering ... 7
II. Acquire Game Experience Features from Text Analysis ... 10
1) Acquire Expert Reviews ... 10
2) W2V Embedding on Expert Reviews ... 11
3) Acquire Experiential Keywords ... 11
4) Keyword Clustering for Experiential Concept Groups ... 12
5) Acquire Game Experience Features ... 13
III. Connect Game Experiential Genres and Game Experience Features with Classification Models ... 14
1) Classification Models of Game Experiential Genres on Core Games ... 14
2) Model Selection and Interpretation ... 15
IV. Portray Game Experiential Genres and the Video Game Experiences ... 18
1) Predict Experiential Genres of Non-Core Games ... 18
2) Describe Game Experiential Genres ... 19
Discussion (Preliminary, not part of the Method and Result section) ... 22
Appendix ... 23
A. Core game list ... 23
B. Survey demographic summary ... 23
C. Triplet distribution ... 24
D. Core game clusters (experiential genre labels) ... 24
E. Keyword search seeds ... 25
F. Experiential keyword samples ... 25
G. Keyword cluster examples ... 26
H. Core game cluster distribution ... 27
I. Confusion Matrices ... 27
J. Experiential genre word clouds ... 30

By extracting information from expert reviews, this research strives for developing an approach to portray video game experiences. To demonstrate the approach effective, I build a classification model that applies information from the review texts to predict video game experiential genres, the general categories of video game experiences.

These experiential genres are identified in this project through a survey, which consults real video game players about the in-game experiences of selected games. Meanwhile, video game experience features are addressed in corresponding expert review texts. These features are taken as input of the classification model to predict the games' experiential genres acquired from the survey. If a sound relationship presents, we can then be confident in the proposed approach.

One step further, this classification model is applied to other games not included in the original survey, to obtain their predicted experiential genres. These predicted genres are then examined to further confirm the established connection and to identify experiential features best distinguishing, or portraying, the underlying genres.

The entire methodological process is organized into four sequencing Stages to be elaborated in following sections: I. Identify game experiential genres from survey, II. Acquire game experience features from text analysis, III. Connect game experiential genres and game experience features with a classification model, and IV. Portray game experiential genres and the video game experiences. The flow of the four Stages is summarized in Figure 1.

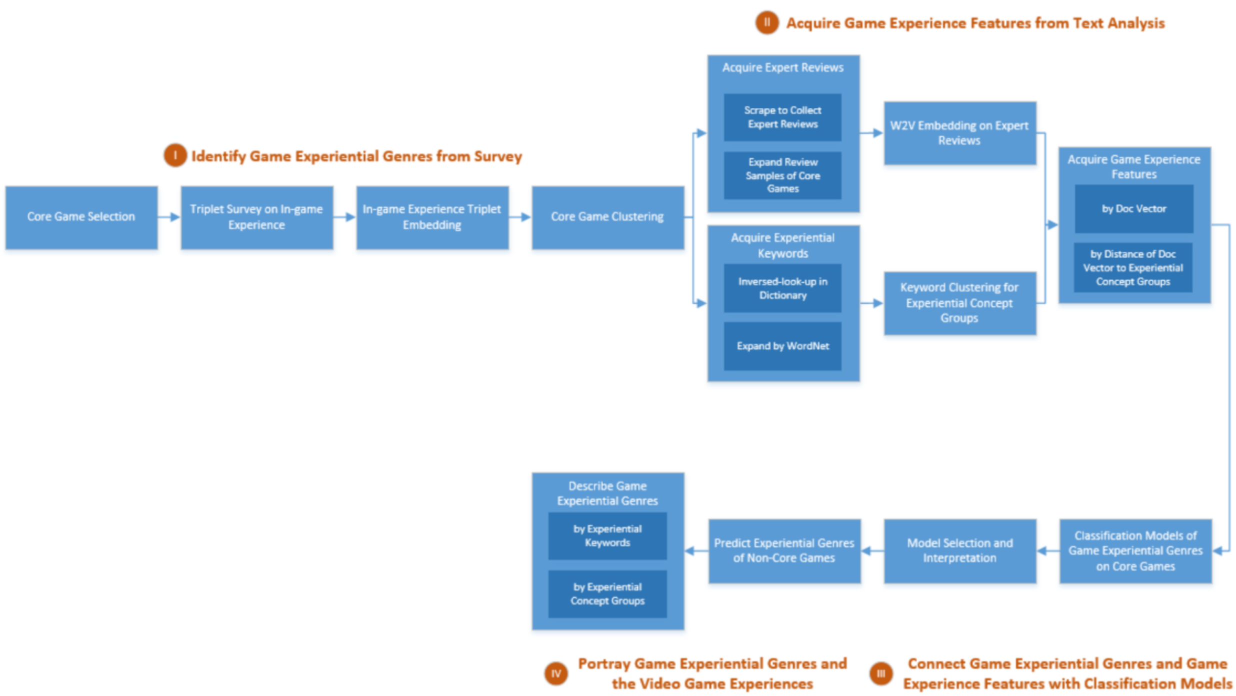


Figure 1. Methodological Process Summary

I. Identify Game Experiential Genres from Survey

Figure 2. Stage I Process Summary

To identify potential game experiential genres, at Stage I, a survey is conducted through Amazon Mechanical Turk (MTurk). Regarding in-game experience, this survey collects information about the degree of similarity between each pair of 50 hand-picked core games through a triplet form. Via t-Distributed Stochastic Triplet Embedding (t-STE), the triplet-similarities are constructed into a high-dimensional space, where the distance between the core games preserves similarity of experience between those games. Based on where they locate in this embedding space, the core games are clustered into seven groups, each denoting one potential video game experiential genre that serves as an outcome variable in the classification model later in this study. Further method details and results of Stage I are provided in sub-sections below.

1) Core Game Selection

A small subset of video games is manually selected to be used in the survey for similarity in the nature of in-game experiences. To be fit into the length of a survey, the core games are highly selective based on several criteria. First, the selected games have to be popular, a standard applied in this research is that they have to be sold an upwards of 4 million titles, since I want the survey respondents to have enough relevant knowledge in the highlighted games to provide reliable judgment about their in-game experiences. Second, the experiences delivered in those selected games have to be diverse to be representative and to cover different types of experiences appear in the assorted video game worlds. Responding to this requirement, one practical strategy implemented here is to select games across game platforms (e.g. Play Station and Wii) and traditional video game genres (e.g. First-Person Shooter and Role-Playing Games). In addition, even in the same genre, nuanced differences between each specific game and its in-game experiences are taken into account, when the author makes the final selection verdict.

Premised upon these standards, 50 video games are chosen and hereon known as "core games". Including popular games such as *Diablo III*, *Angry Birds*, *Half-Life 2*, *New Super Mario Bros*, *League of Legends*, *The Elder Scrolls V: Skyrim*, a full list of the 50 core games is provided in Appendix A.

2) Triplet Survey on In-game Experience

Next, I enlist the help of survey participants on MTurk to determine a good similarity function between objects that would help in producing experiential clusters. I want to cluster games according to their in-game experiences, but having players describe them one game at a time would be too onerous a task. Instead, I create pair-wise comparison questions that tasked participants to compare in-game experiences and decide which were similar. This helps to reduce fatigue on survey participants, at the same time alleviating the need to reconcile individuals' scales of similarity.

The intuition behind the triplet question form is this: imagine if you are a game store to buy a game for a friend, but the game you have in mind is out of stock. Which other game would you choose based on the similarity of in-game experiences to your original title? Out of the 50 core games, participants selected 5 that they are well-acquainted with and compared them with others. For example, "based on your in-game experiences, is *Half-Life 2* more similar to *RollerCoaster Tycoon* or *Metal Gear Solid*?" In addition, to avoid suboptimal responses, participants must pass a bar of correctly answering sufficient factual questions about the 5 games they selected[1]; to ensure information of each game is collected evenly and therefore the quality of subsequent analyses, the triplet distribution across all core games are closed monitored by the author, and the games presented in a survey event for the respondent are decided accordingly.

As a result, the survey[2] has a total of 350 participants, each making 20 triplet comparisons. Filtering out invalid answers, 6,990 triplet comparisons are received. Demographic description of the survey participants and the triplet distribution is provided in Appendix B and C, respectively.

3) In-game Experience Triplet Embedding

Preparing for clustering to identify the game experiential genres, I employed t-STE on the survey results. This method, developed by Laurens van der Maaten, specifically adjusted to the task of extracting the information from triplet comparisons. This method generates an embedding space that refines the variation between observation points in the original triplet raw data and preserves similarity between each object, video game in this research, in the form of distances between those objects in the embedding space. It outperforms GNMDS (Generalized Non-Metric Multidimensional Scaling), CKL (Crowd Kernel Learning), and other existing techniques on the specific triplet data form.

Deciding the number of features (dimensions) to be extracted from this algorithm, I calculate the error rate, the percentage that the triplet response is wrongly described by the Euclidean distances between the focal objects. 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*. The result of the error rate by a different number of features extracted is provided in Figure 3. Conforming to intuition, the error rate decreases as the number of feature increases. In addition, this decrease slows down when the number of feature goes up; the error rate stays almost constant when more than 25 dimensions are extracted. Consequently, for following analyses, I adopt 25-dimension version of the embedding, which achieves a computational efficiency as it captures sufficient information from the original triplets to acquire a remarkable 80% correct rate of describing similarity with the least number of dimensions.

[1] The bar is high; the passing rate of the screening is only 36.57%.
[2] The questionnaire can be accessed through: https://chicagobooth.az1.qualtrics.com/jfe/form/SV_8v8Hp7GDd-paNPoN.

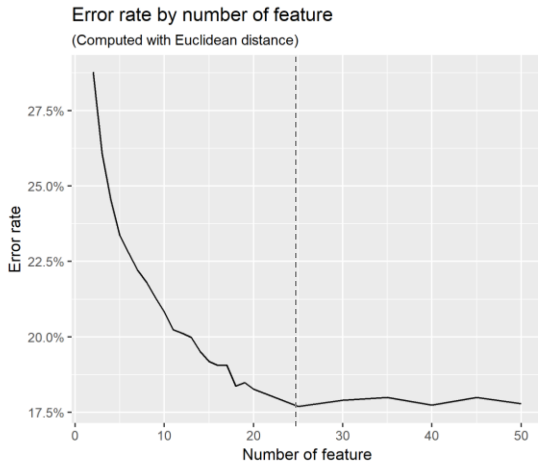


Figure 3. t-STE Error Rate by Number of Features

A projection of the embedded experience similarity between the core games is shown in Figure 4 by the 2-dimention version of t-STE embedding. Although with only 2 dimensions, where nuance information must be left out, 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 further strengthens our confidence that the t-STE appropriately captures the experience similarity between the focal games.

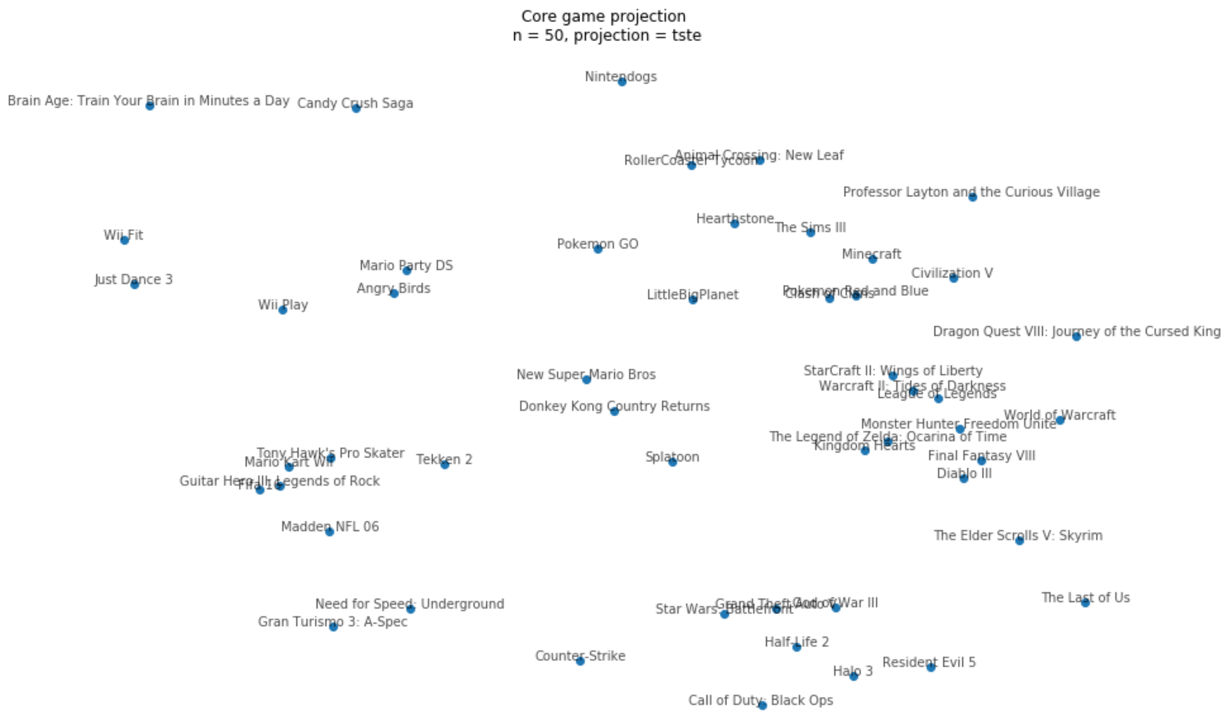


Figure 4. Core Game Experience Projection

4) Core Game Clustering

Based on the embedded vectors obtained from the triplet comparisons on the in-game experiences, I conducted a hierarchical clustering via the Ward variance minimization algorithm to group the core games into game experiential genres. To determine the proper number of clusters, I combine subjective judgment with information from the elbow method. In Figure 5, the blue line is the growth of distances from the difference of merging distance between the previous two merges to the difference of merging distance between the last and the current merge, which produces the target number of clusters; the orange line depicts the distance growth acceleration, the first order derivatives of the blue line. While the growth acceleration peaks at acquiring 2 clusters and then 5 clusters, the final number of cluster is set to be 7, the third rally in the acceleration, since the more meaningful and explainable clusters resulted from it, regarding the in-game experiences conveyed in the clustered games. The full clustering result is provided in <u>Appendix D</u>.

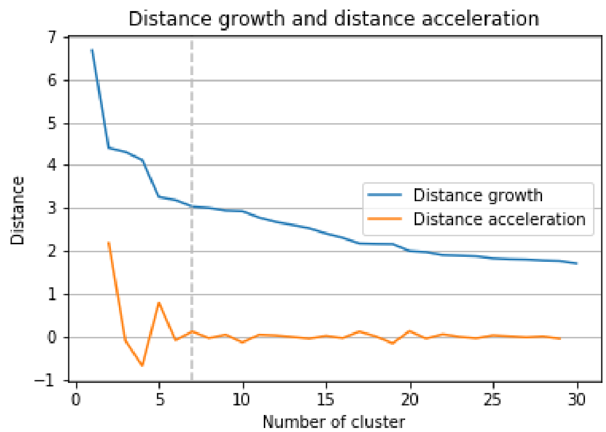


Figure 5. Distance Growth and Distance Acceleration of Clustering Merges

Again, I use the 2-dimention version of t-STE vectors to project the core games onto a two-dimensional space, with the color representing the 7 different game experiential genres, as shown in Figure 6. Aside from several overlaps, the clusters are relatively distinct. This distinction between experiential genres indicates the satisfied quality of the clusters, each characterizes a distinct stress in the experiences.

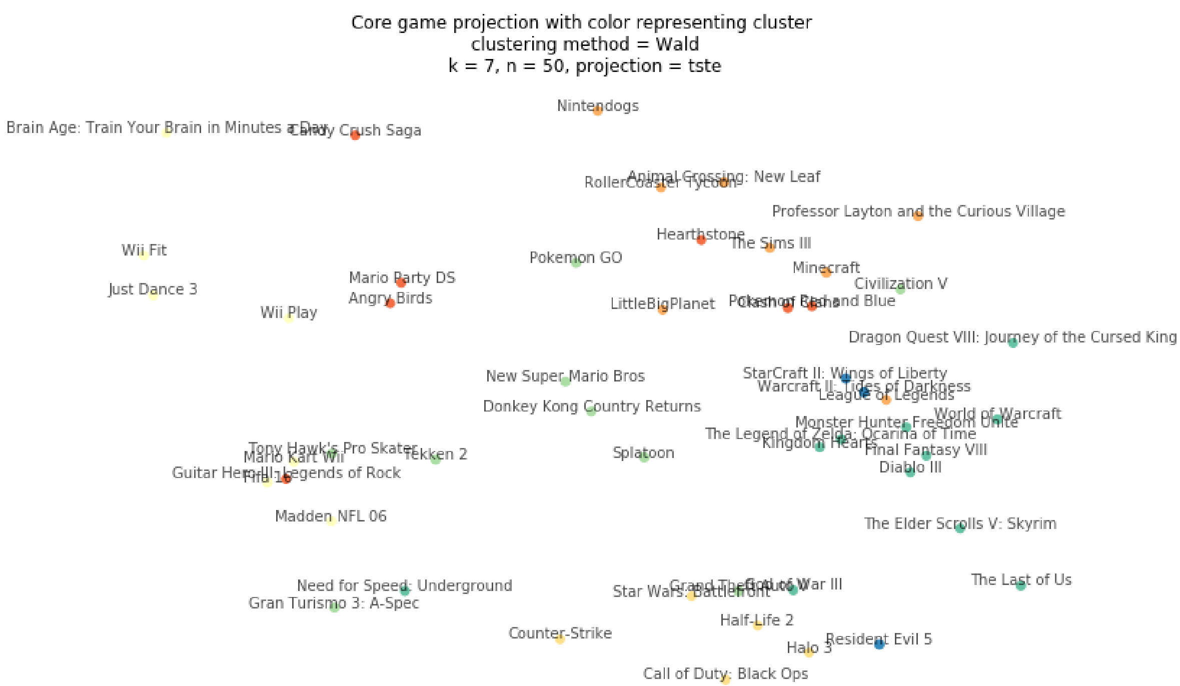


Figure 6. Core Game Projection with Cluster Labeling

For example, the orange genre in the figure can be considered to denote a creation, or creative, experience of the games. This orange genre includes 8 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 5 players in a team, each with 136 possibilities: it is the 136 to the power of 5!

Table 1. Orange Genre Game List

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

II. Acquire Game Experience Features from Text Analysis

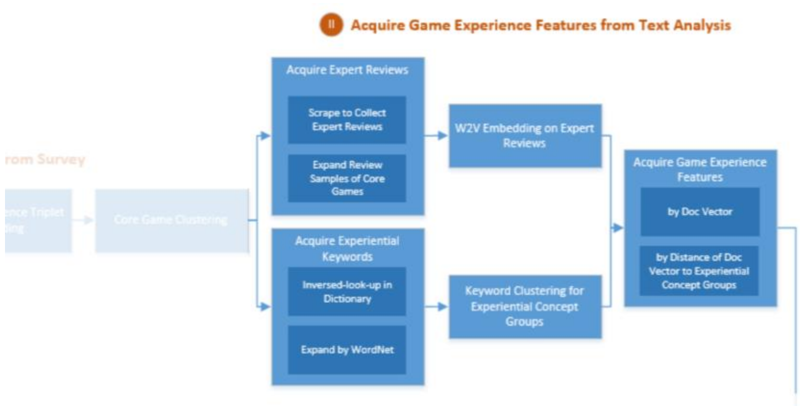


Figure 7. Stage II Process Summary

In Stage II, two approaches of text analysis are adopted in acquiring game experience features—the actual experiences delivered in a video game. Both approaches make use of a Word2Vec (W2V) word embedding space trained with a large corpus of video game expert reviews, collected by the author from major video game information websites in the U.S. This specific W2V trained by the reviews is a high-dimension space representing semantic similarity between words apropos of linguistic conventions of video gaming field. One approach utilizes the Doc2Vec (D2V) algorithm acquire document vectors, each denotes the semantic position of a review article in the W2V space. Dimensions of the document vectors are identified as the experience features of the corresponding games in the first approach. The second approach adopts a document's distance from each "experiential concept groups" as experience features of the game corresponding to this document. In a systematic way, a list of "experiential keywords" is curated, and the keywords are clustered into the experiential concept groups, which are then used to develop the experience features as mentioned. Further method details and results of Stage II are provided in sub-sections below.

1) Acquire Expert Reviews

Expert reviews of video games are the pillars of this entire study. More than evaluating the value of a game, reviews help to convey in-game experiences to its readers. They typically relay the various experiential dimensions within a game: kinds of in-game systems the game has, the various challenges players will encounter, storylines, and the various intricacies of the game's social world.

During this study, more than twenty thousand game reviews are scraped from GameSpot, Polygon, and GamesRadar, three of the major video game information platforms in the U.S. These websites are independent and have no direct interests in developing or selling video games. To control the effect of a specific author, his/her writing style, vocabulary, and attitudes influencing the quality of review articles as the impartial representation of the corresponding games, the final corpus includes only one article of a specific author writing for a specific game. As a result, by 671 authors, 15,727 game reviews covering 11,727 unique games are employed in the following analyses. Video games represented by the reviews are across platforms, traditional game genres, and, apparently, video game developers and publishers.

Through these game reviews, I amass a total of 14,616,961 words of analysis. The length of reviews averaged 929 words—meaning that on average, 929 words capture the essence of in-game experiences in a game. Stopwords are removed using the NLTK English stopword dictionary; no stemmers and lemmatizers are used as I intend to preserve the information from the sentence structures. The cleaned corpus contains 6,122,321 words and is presented by a word cloud in Figure 8. Beside GAME, GAMEPLAY, PLAYER, and obvious top words belong to a video game corpus, LEVEL, SOUND, WEAPON, STRATEGY, ONLINE, MISSION, ENEMIES, COMBAT, CARS, and many other words together constitutes a strong "video game flavor" of the underlined video game expert review database.

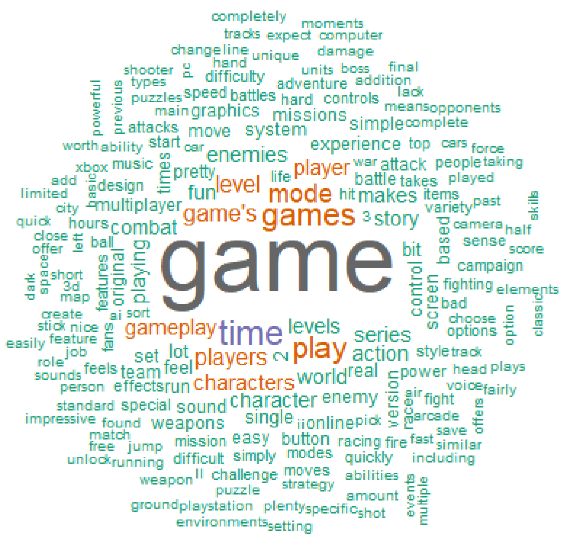


Figure 8. Game Cloud – Video Game Corpus

Furthermore, since I can only have 50 core games in the survey, to make the models derived from the corresponding review texts more robust, the review article database for these 50 core video games is 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 (game) in the later model building process.

2) W2V Embedding on Expert Reviews

The cleaned expert review corpus as the input, I performed a sentence-based W2V embedding with the negative sampling method to acquire 300 features, or dimensions. W2V embedding derives high-dimensional spaces to capture semantic nuances expressed in raw texts. Each specific word exists in the corpus can be located in the embedding space and, in other words, represented by a specific word vector. One major advantage of the W2V embedding is the resulted distances between the word vectors parallel the semantic differences between the corresponding words. In this research, I rely on this specific characteristic to extract video games' experience from the corresponding review texts, transforming semantic meanings of experiences into operable numeric matrices.

3) Acquire Experiential Keywords

However, not all content in the reviews is amenable to my goal of identifying the experiences delivered in the games. That is, not all descriptions within reviews concern experiences—many are evaluations of a game's value, such as the price of a game or the production quality of a game. These factors could negatively influence the accuracy of the later models based on the entire review texts, and affect their prediction outcome. As a result, I try to parse through the content using "experiential keywords" to sieve out the unrelated compositions.

To implement this tactic, I first 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 (see Appendix E for the full list) 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 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. Some randomly selected sample keywords are shown in Table 2; More examples can be found in Appendix F.

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

4) Keyword Clustering for Experiential Concept Groups

With more than thirty thousand experiential keywords, I tried to further categorize them into groups. The direct benefit of grouping the experiential keywords is twofold: to sieve out the noise brought in by a large number of features and to avoid over-weighting the experiential concepts expressed in more words than others do. To overcome this, the identified experiential keywords are clustered based on their locations in a W2V space trained by Google with 100 billion words from a Google News database. I apply a word embedding space different from the one from game review articles so that I could acquire a more general and precise relationship between the experiential words—the Google News word embedding represents a more generalized usage of these keywords. Compared to the Google News word embedding, the game review word embeddings contained more video game specific semantics, which could be misleading due to their particularities (especially their cultural usages) when categorizing these experiential keywords.

Next, experiential keywords are clustered, again, with the Ward algorithm. 10, 30, 100, 300, and 1000 clusters are acquired respectively. 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 from 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. A couple of other example clusters can be found in Appendix G.

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	

5) Acquire Game Experience Features

Finally, two approaches are adopted to acquire the game experience features, the actual experiences delivered in a video game. One applies document vectors or review articles directly derived from the W2V space with a Doc2Vec (D2V) algorithm. In W2V space, a document vector is the centroid of all word vectors belonging to the words constitute this specific document text, and, therefore, represents the average semantic orientation of this article. As expert reviews are linguistic concretizations of experience delivered in the corresponding video games, their document vectors can be 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. On the other hand, its summarizing characteristic becomes its major drawback as the experience features obtained from it are arbitrary and cannot be explained meaningfully, because dimensions of a W2V space are themselves arbitrary and cannot be further expounded.

Also implemented in this current research, another approach adopts a document's distance from each "experiential concept groups" as experience features of the game corresponding to the document. I compute the centroid of each experiential keyword group in the game expert review word embedding space and calculate cosine similarities (distances) between review document vectors and each of the keyword group centroids. These results were then taken to be the features to be used in the following model. 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 a concept group and uses the meaning of these words to define this specific feature. However, calculation of distances for the features can be computationally expensive when the experiential keywords are many.

III. Connect Game Experiential Genres and Game Experience Features with Classification Models

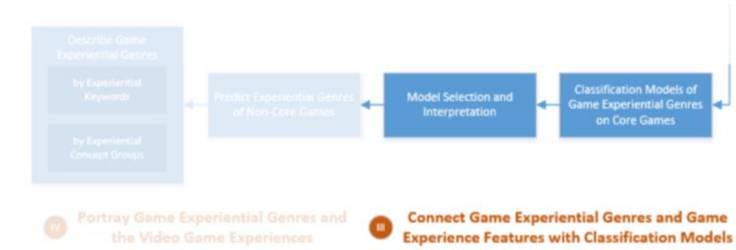


Figure 9. Stage III Process Summary

In Stage III, multiple models are employed and validated in a classification task of predicting game experiential genres of the core games with the game experience features extracted from the corresponding expert review texts. Through this classification model, the game experiential genres, developed in Stage I, and game experience features, derived in Stage II, are connected. This important connection illustrates the effectiveness of using the expert review texts to describe the experiences delivered in video games. It opens up further applications of applying text analysis in retrieving experiences, an abstract construct difficult to be assessed in traditional approaches. Further method details and results of Stage III are provided in subsections below.

1) Classification Models of Game Experiential Genres on Core Games

With 355 core game review articles as observations, I employ the two sets of game experience features, in the game review embedding space, to build a classification model in predicting core games' experiential genres. Each of both the document vectors and the distances between document vectors and each experiential concept groups is plugged into four classification models: linear kernel Support Vector Machine (SVM), Neural Nets (Multi-Layer Perceptron (MLP)), Random Forest[3], and Multinomial Naive Bayes. To further evaluate model performance, four versions of experiential concept groups are implemented in each of the models, with 10, 30, 100, 300, and 1000 features respectively. Their performances are compared with of the document vector approach (300 features). Furthermore, each model is implemented with a leave-one-out cross validation. Model precision rates are evaluated in all conditions and are computed by averaging precision rates of all 7 experiential genres with constant weights.

The prediction results are satisfying. In general, the Neural Nets model with document vectors as the input performs the best, with a 58.31% precision rate, a huge improvement from the baseline rate of 23.38%, by classifying all samples into the experiential genre with the most observations belongs to it. It also outperforms all models with other classification methods or with concept group distances as the input. Presented in Figure 10 are the confusion matrices of all four models applying document vectors as the input. The model functions well in experiential genre 2, 3, 4, and 5, and performs the worst in genre 6. This performance characteristic can be observed in generally all models. Real cluster distribution of the core games is provided in Appendix H. Model performance is further compared and discussed in the next section.

[3] 100 base estimators are trained with 80% of the original sample.

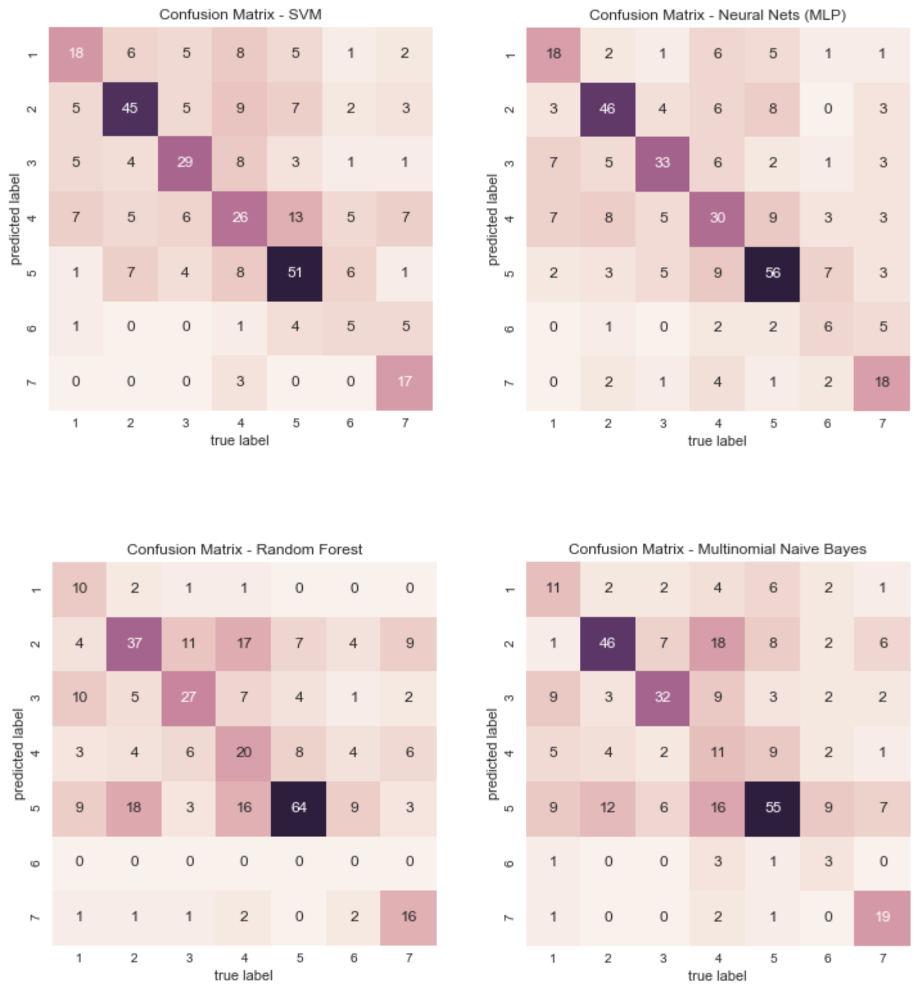


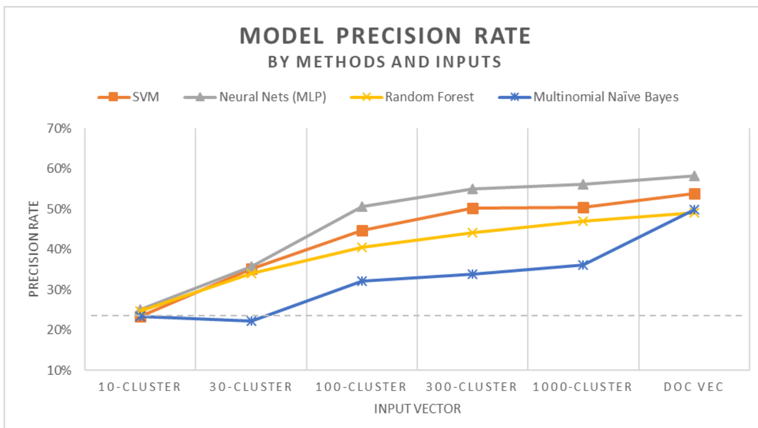
Figure 10. Confusion Matrices - Document Vectors as the Input

2) Model Selection and Interpretation

Performance summary of all models are provided in Table 4 and Figure 11. All models are implemented with the entire 355 core game review database, and all precision estimates are based on all results of the leave-one-out cross validation. With all types of inputs, the simple Neural Nets produces the best results. Its performance is followed by SVM, Random Forest, and then the multinomial Naïve Bayes. The performance difference between the methods is modest, mostly within 10%. That said, the MLP Neural Nets, still, provides the best and consistent output in all situations in this study and is, therefore, considered the best model to be carried over in later analyses. On the other hand, model precision rate increases as including more features in the model. Regarding experiential concept groups as the input, 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.

Table 4 and Figure 11. 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%



To further improve this classification model, one future extension could be an ensemble architecture combining the predicting capability of different methods. Though the general precision rate is lower with the experiential concept groups approach, Indeed, some genres are better predicted by the concept group inputs than the document vectors. For example, Genre 3 is slightly better predicted by the 300-cluster model (Figure 12) [4], compared to the document vector model. The potential ensemble method can simply integrate predicted results of different genres from different models, or accept combined input of document vector and concept group features to account for each models' deficiency in certain genres.

[4] Confusion matrices of 10, 30, 100, and 1000 cluster models are presented in Appendix I.

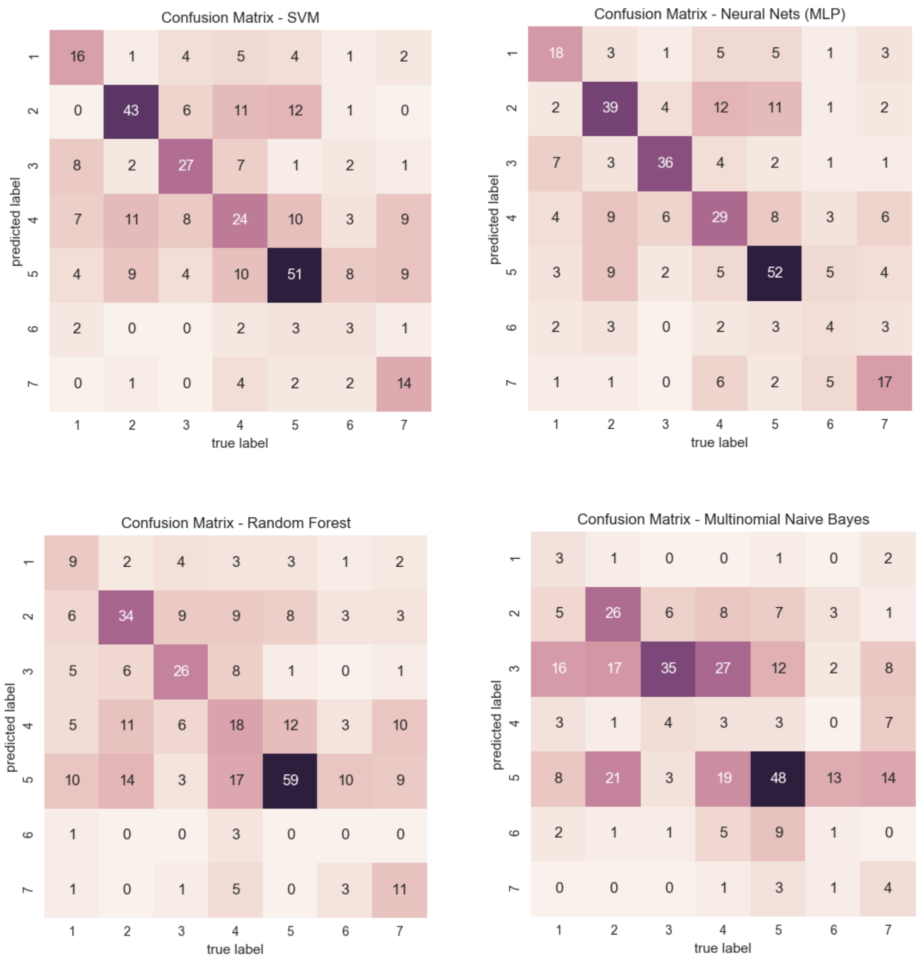


Figure 12. Confusion Matrices – 30-Cluster as the Input

IV. Portray Game Experiential Genres and the Video Game Experiences

Figure 13. Stage IV Process Summary

In the final Stage, the best classification model is employed with the other non-core game reviews as the input. There are no true genre labels can be used to validate the model. However, from the visualized distribution of the non-core games' predicted experiential genres, one can further evaluate the quality of describing video game in-game experiences through the expert review texts. Moreover, through analyzing the review texts of a specific experiential genre, the genre's characteristics are described and discussed. Further method details and results of Stage IV are provided in sub-sections below.

1) Predict Experiential Genres of Non-Core Games

With the best performance combination, document vectors input and the Neural Nets method, the classification model is applied to the 15,727 game reviews, covering 11,727 unique games. This effectively gives us the prediction of experiential genres of games outside the 50 core game set. In Figure 14, I present the classification result via a t-SNE dimension reduction, a technique proposed by the same author of the t-STE embedding, which provides a better projection in this video game text analysis case. In the figure, a dot represents a review article, with the predicted experiential genre as its color. Location of a dot is the 2-dimensional t-SNE projection, reduced from the review's corresponding document vector. Some popular games are randomly selected to be marked on the map.

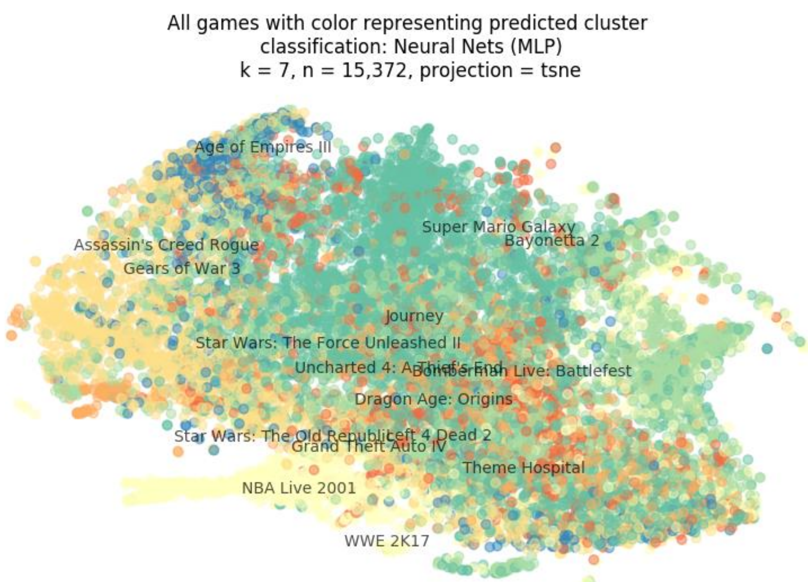


Figure 14. Non-Core Games Projection - Document Vectors as the Input

In general, the results are promising. 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.

With this visualization, we can also gain some superficial insights to the quality of the underlying classification model. This geographical separation between genres indicates a good quality of the classification. It successfully captures sufficient between-genre variation, confirming the same variation illustrated by the spatial allocation of the observations in the projection. 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 15) 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.

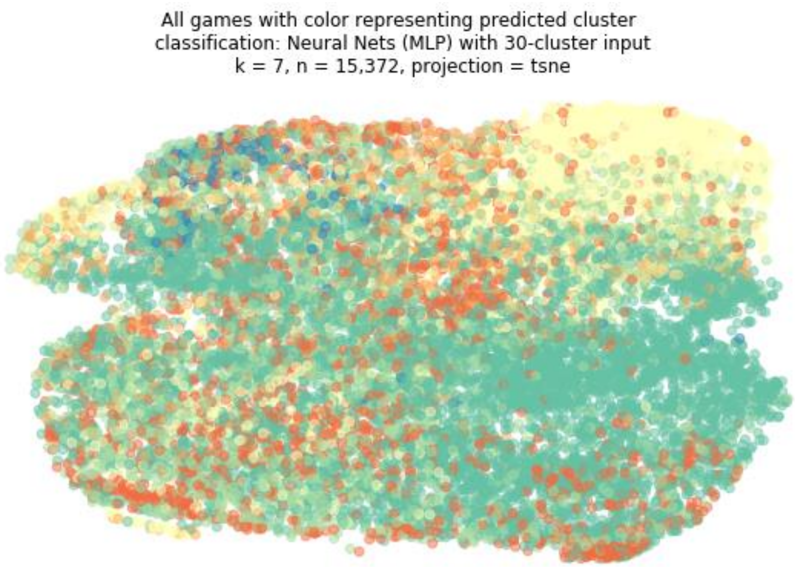


Figure 15. Non-Core Games Projection – 30-Cluster as the Input

2) Describe Game Experiential Genres

The game experiential genres can objectively be described by the experiential concept groups and individual experiential keywords identified in this study. Regarding the experiential concept groups, Figure 16 presents the average scores (cosine similarity to the concept group in the video game W2V space) of each experiential genre on ten concept groups excerpted from the 300 clusters of experiential keywords. These ten concept groups are particularly selected because of their highest within-group variation across different genres for better visualization and interpretation. Experiential concept groups are lists of words each representing a specific experience-related concept, which can be applied in describing the game experiential genres identified and classified via mostly arbitrary and non-explainable vector scores extracted from expert review texts. For example, as described in the previous section, Group 292 expresses an experience of "frolic foods"; containing words like DIVINE, TRINITY, FEUDAL, and MINISTRATION, Group 11 represents the experience of "deity/human hierarchy"; comprising of words such as SUPERNATURAL, AFTERLIFE, WITCHERY, and NECROMANCY, Group 60 could denote the "mysterious" experiences; with CARNIVAL, JAZZ, MAMBO, GOSPEL, and JUKEBOX, Group 101 illustrates an experience of "music and dance"[5]. Matching onto the experiential genre, for instance, the "creative" Genre number 2 (including games such as *The Sims III* and *LittleBigPlanet*) has the lowest score of all genres on Group 11, the "deity/human hierarchy" experience, also low scores on Group 60, "mysterious" experience, and Group 101, the "music and dance". 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 101 "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.

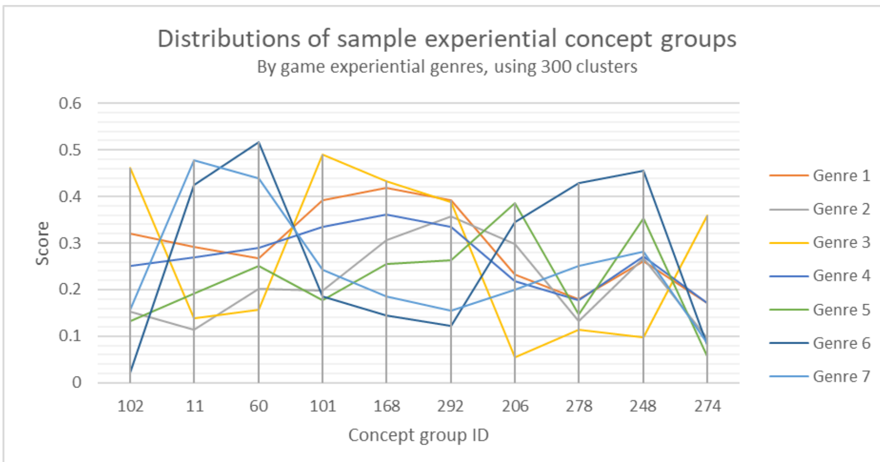


Figure 16. Distributions of Sample Experiential Concept Groups

Also developed in this research, another approach to describe characteristics of the experiential genres is via the experiential keywords themselves. By simply presenting high-frequency words in the review texts representing each experiential genre, experience flavor of a specific genre can be revealed. Figure 17 presents the word cloud developed from the Genre 1 review articles. Its word cloud features words like TIME, SERIES, and LEVELS, demonstrating the members' episodic gameplay style, for example, *Angry Birds* and *Candy Crush Saga*'s repetitive, periodic, and small game sessions. On the other hand, Figure 18 shows the word cloud of the Genre 2, the creative genre. Some highlighted words, such as CREATE, WORLD, BUILD, and LIFE, signifies the experiential nature of the member titles, such as *Minecraft* and *Animal Crossing: New Leaf*, which simulates a village community and, among it, the villagers' life. Experiential keyword clouds of other genres are also provided in Appendix J.

[5] The exemplified concept groups and the element keywords within each group are provided in Appendix G.

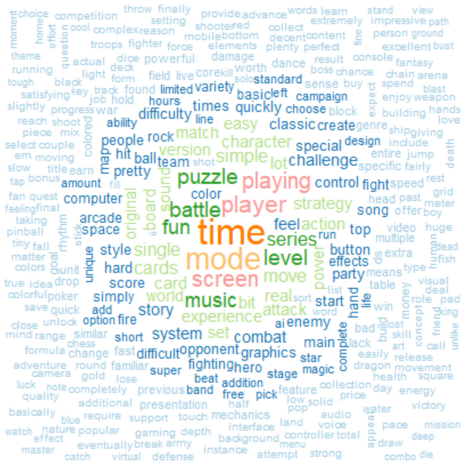


Figure 17 and Figure 18. Word Cloud - Genre 1 and Genre 2

Discussion **(Preliminary, not part of the Method and Result section)**

From the above process, three major contributions are proposed in this study. First, seven potential game experiential genres are identified. Theses genres are extracted from triplet comparisons done by real video game players and are expected to be more complete and objective, compared to other experience categories proposed in the current literature, the forming of which often involves more abstract questions to be answered by the respondents and more researchers' personal judgment on selecting items to be asked in the surveys. Second, this study validates the connection between video game in-game experiences and the corresponding expert review texts. 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 between 55% to 60%, compared to the baseline as 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. Via this full-scale application, third, this study demonstrates an economical way to portray video games' in-game experiences. The video game experiences are illustrated by the distance to each experiential concept groups, also developed in this study, acquired with a systematic approach for a quality and universal view of human experiences. The distances can be obtained with only the review texts as the input, which can easily and cost-effectively be attained, in contrast with conducting real player surveys and along with it all the financial expenses and logistics problems.

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. 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

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

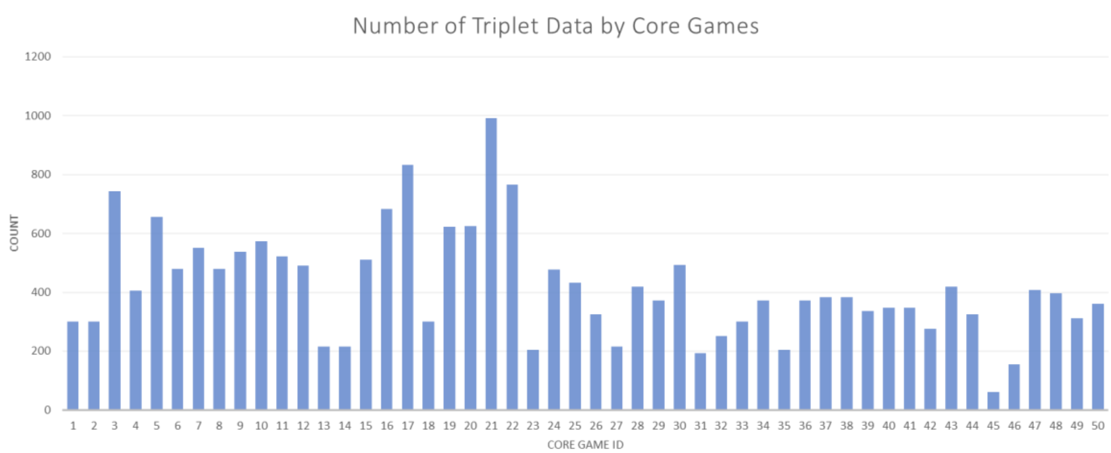
Income	
< 10,000	15
10,000 - 19,999	21
20,000 - 29,999	35
30,000 - 39,999	24
40,000 - 49,999	24
50,000 - 74,999	50
75,000 - 99,999	26
100,000 - 149,999	16
> 150,000	4

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

C. 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



D. 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		

E. Keyword search seeds

The terms used in the reversed-search for identifying experiential keywords.

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

F. 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

G. Keyword cluster examples

“Deity/human hierarchy” experiential group:

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						

“Mystical” experiential group:

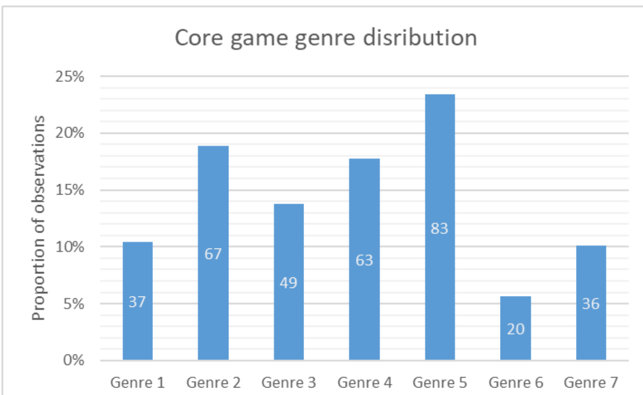
VAMPIRISM	CONNOISSEURSHIP	ABSTRACTIONIST	PORTRAITURE	CABALA	SYMBOLIST	KABBALISTIC	WITCHERY
SPIRITUALISM	DRAFTSMANSHIP	NONOBJECTIVE	CLASSICIST	KABBALA	TRANSUBSTANTIATION	ANIMIST	CONCEPTUALIST
SPIRITISM	ANATOMIST	MIDRASH	THEOSOPHY	KABBALAH	POLYMATH	TANTRA	
MYSTICISM	KABBALIST	DYBBUK	KABBALAH	LANDSCAPIST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

“Music and dance” experiential group:

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

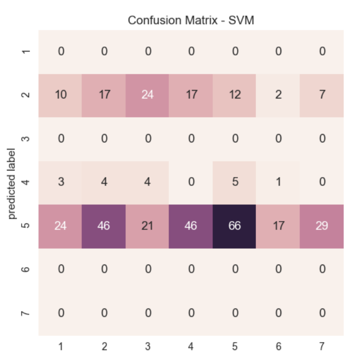
H. Core game cluster distribution

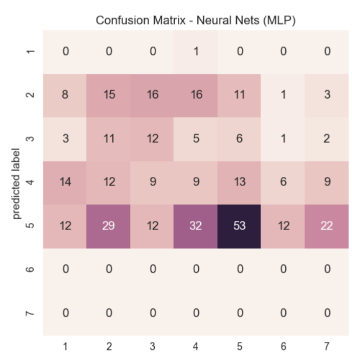
The distribution of core game genre labels. The unit is one expert review article.

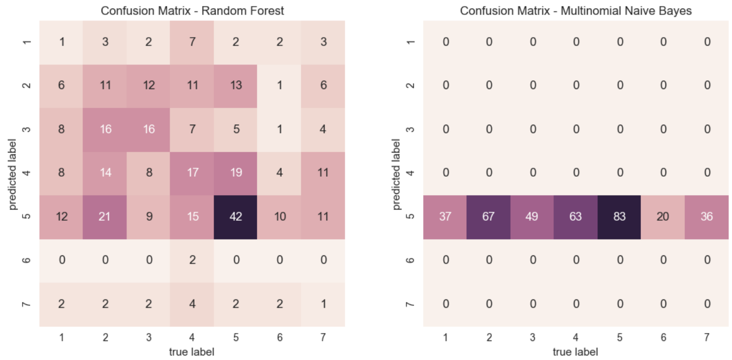


I. Confusion Matrices

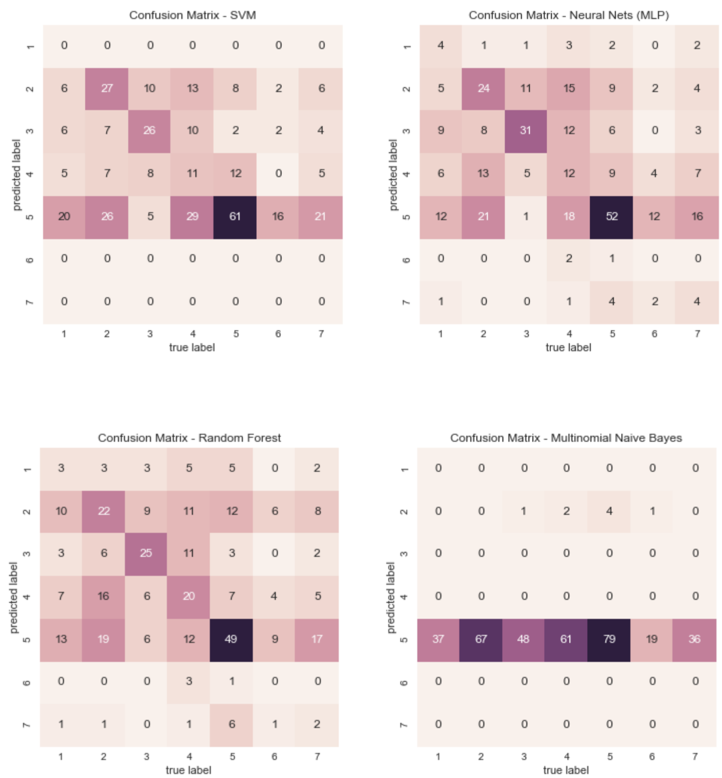
Confusion matrices of models with 10-cluster as the input.



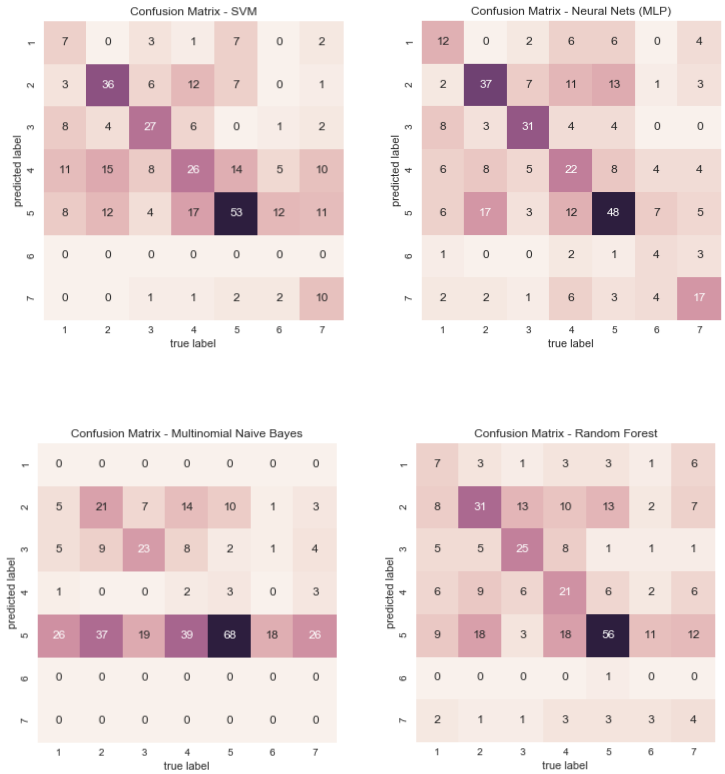




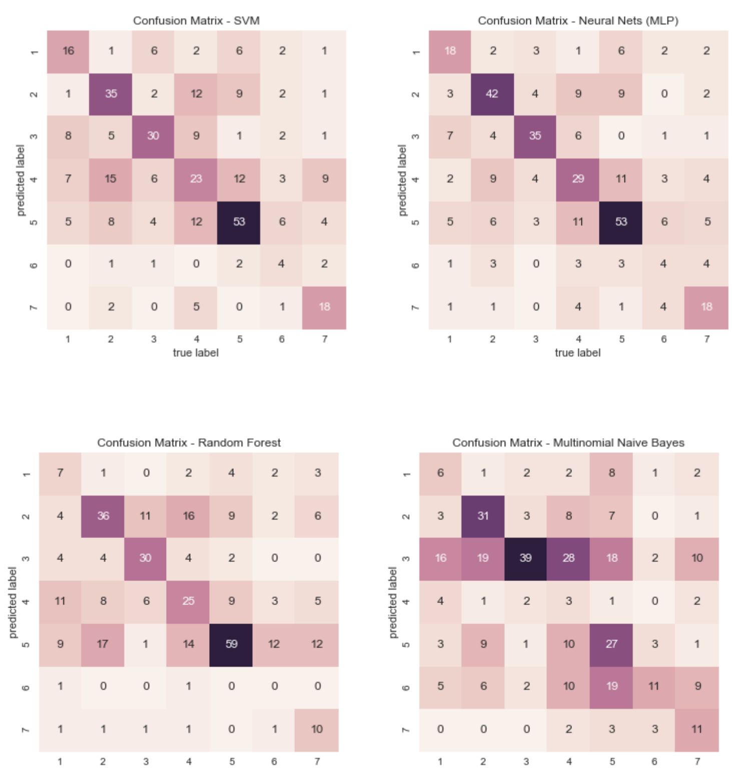
Confusion matrices of models with 30-cluster as the input.



Confusion matrices of models with 100-cluster as the input.



Confusion matrices of models with 1000-cluster as the input.



J. Experiential genre word clouds

The word clouds below are developed from Genre 3 to 7, arranged from left to right, according to the Genre order.