INSY 669-075 | Text Analytics

Presented to Professor Changseung Yoo

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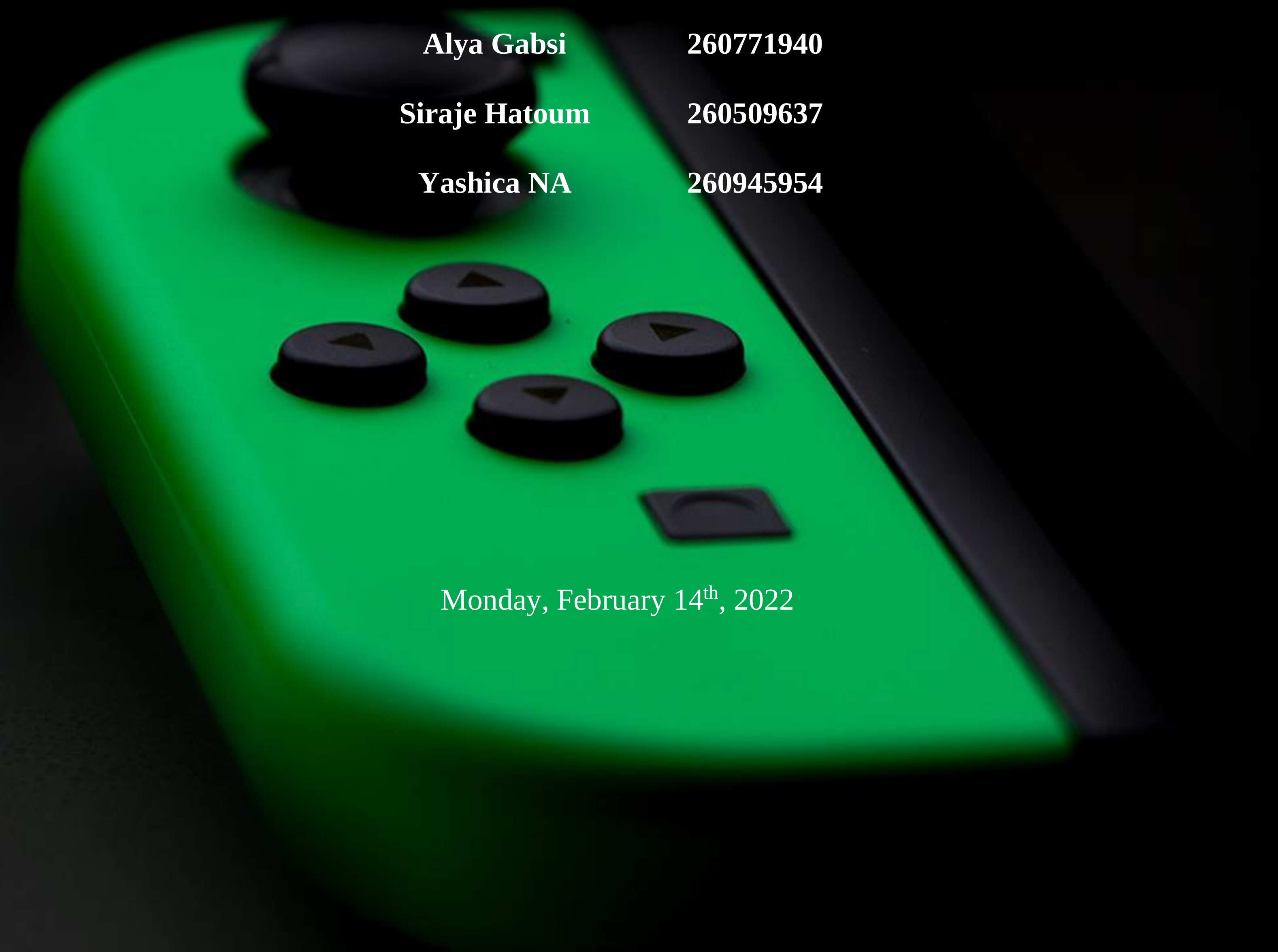

Monday, February 14th, 2022

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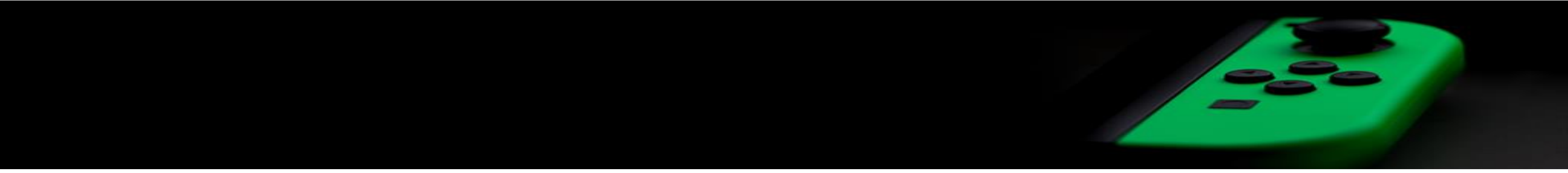


Project Overview

Industry Context

In 2020 the global video game market was valued at $ 156 billion with a projected valuation of $ 267 billion by 2025 (Juniper Research, 2021). In large part, this growth is due to the decreasing cost of gaming hardware enabled by the advent of mobile phones and cloud-based gaming, which in turn increases industry penetration into the mainstream.

In recent years the growth of the industry has accelerated due to Covid related stay-at-home advisories and lockdowns. Video games emerged as a tool to "connect with friends remotely and socialize online." (Statista, 2020).

The size and diversity of the market drives growth in the volume and variation of game products targeted at a range of consumer preferences. This abundance of choice can lead to decision paralysis in the absence of information, pushing customers to seek multiple sources to inform and influence their purchase decisions.

One popular source of consumer information is the published game review, which provides in-depth analysis of gameplay experience from a qualified journalist. A survey conducted in 2016 revealed that 26% of participants frequent these gaming publications to inform their purchasing decisions (Statista, 2017). Current game-related search trends suggest that this reliance on game reviews persists today, with the top 10 most searched games in 2021 averaging 16 million monthly search volume worldwide (Semrush, 2021). This demand has spurred the growth of multiple publications and websites, such as IGN and Gamespot, whose primary value proposition revolves around generating game reviews for potential buyers.

Metacritic is a review aggregator much like Rotten Tomatoes, that generates an overall rating (Metascore) based on the mean rating provided by multiple independent publications. The site aims to reduce the reliance of potential buyers on the opinion of a single publication by incorporating the outlook of multiple sources to reduce potential bias and increase reader confidence in the critic score.

Problem Statement

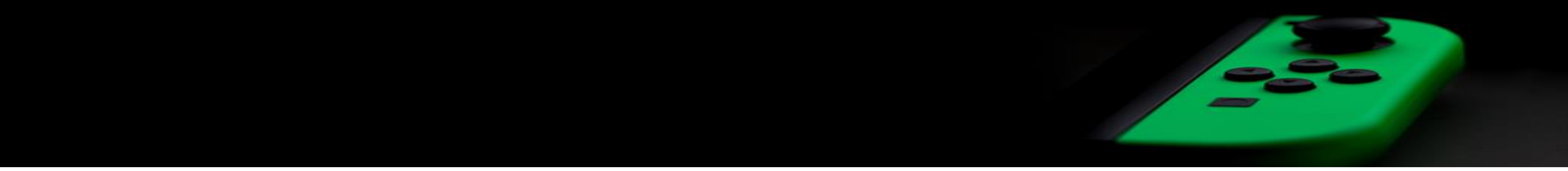
A major shortcoming of Metacritic's current offering is the lack of transparency when using the Metascore as a key metric. In other words, the aggregated score does not provide enough information to guide consumer purchase decisions due to an absence of insight regarding the strengths and weaknesses of the game which are often weighted differently based on customer preference.

In response to this issue, Metacritic extracts short blurbs from each of the underlying reviews to help summarize its key points and provide more actionable insights. Ultimately, this means that readers are still having to read, albeit shorter, extracts from multiple reviews to get a better understanding of the games defining attributes.

This project aims to improve the user experience of Metacritic readers by providing separate ratings on a number of game attributes (e.g. gameplay, narrative, technical performance) based on each game's review blurbs. The feature will be implemented using text analytics techniques to automate the process and reduce overhead cost of updating and maintaining these scores.

Solution Approach

Using topic modeling we aim to identify a list of game-defining attributes and the words most associated with them in critic reviews. Once defined, the topic-to-word mapping will be used to extract text segments that are related to each topic. Sentiment analysis will be performed on each segment to produce a sentiment score. The sentiment scores are then aggregated by game to arrive at a rating for each identified attribute.



To demonstrate the potential value of this feature we incorporate the attribute ratings into several use cases and evaluate the resulting improvements and insights.

Metascore prediction modeling: We use the newly generated ratings as features to generate a Metascore prediction model. This use case allows us to assess the value of insights provided by the ratings based on the ability of the features to account for variations in the target variable as well as the relative importance of each game attribute on critical reception.

Game clustering and recommendation: We perform clustering and similarity analysis based on the newly generated ratings to evaluate the validity of the information provided thorough the generated clusters and the value of the recommendations to inform recommender systems for potential customers.

Time Series Analysis: We perform a descriptive analysis of multiple releases of a game franchise using the same newly generated ratings for each game to provide insights into the evolution of the game. This use case highlights the descriptive value of the newly generated ratings and potential use when analysing the strengths, weaknesses, and evolution of game franchises, developers, publishers, genres, etc.

Extended Applications

We believe that the methodology applied, and insights extracted from this analysis can be extended beyond the explored use cases and industry. We envision this approach can help product and brand managers of consumer products that have a high availability of published or crowd-sourced reviews (restaurants, hotels, consumer tech, online retail, etc.) to gain valuable insights into the strengths and weaknesses of their offerings, brands, and competitors.

Extensions on this approach may also be applied to a variety of information sources such as social media posts, published financial documents, news articles, etc. as a tool to quickly condense a large volume of information into a focused list of key takeaways.

Data Source

This analysis was conducted on data extracted from the Metacritic site on PC games released and reviewed in 2021. We extracted data points on 5507 reviews across 321 games. Data details and descriptions are included in Appendix A, Table 5.

Data preprocessing

The data preprocessing was done using a common pipeline of firstly removing the stop words & punctuations from the review summary and creating word tokens using the NLTK library. Using the same library, we used the WordNetLemmatizer to lemmatize the tokenised reviews to reduce the size of the vocabulary. We retained the case of the reviews since it was essential to understand the sentiments of the critics especially when the sentiments are on the extreme side of the spectrum. During the topic modelling process, we found a few words such as "good", "best", etc. that did not add value to the topic qualitative description and therefore were added to the default list of English stop words provided by NLTK library.

Packages explored:

1. NLTK: word_tokenize, stopwords, WordNetLemmatizer
2. WordCloud
3. PyLDAvis & Gensim's LDA model
4. OpenAI GPT3's API

Topic Modeling

The first step in accomplishing the project objectives is to identify a list of frequent and relevant topics that can be linked to game attributes and the words associated with them. LDA topic modelling is well-suited for this task as the word-to-topic distribution output can be used to generate a topic-to-word mapping.

The key parameter input to the LDA topic model is the number of topics mentioned. An iterative and actively supervised approach was used to arrive at an ideal topic number. We experimented with and interpreted the results of multiple topic number parameters based on the preprocessed reviews dataset. The validity of the output was assessed by manually examining the key words associated with each topic and evaluating the internal coherence of topics as well as the inter-topic differentiation. The diagrams shown in Figure 7 in Appendix C illustrates the output of the topic modelling.

Following this approach, we arrived at an ideal topic number of 20. We assigned words to topics based on the topic that had the maximum likelihood of being associated with each word.

The mapping was further refined by manually updates to remove topics that were not closely related to any relevant attributes, ensuring that words within these topics were manually reassigned if they bore a similarity with other topics. Once this process was completed the topics were given representative titles to reflect the theme of the words that were grouped under them. Table 7 and Table 8 in Appendix C list the details of the derived word-to-topic mapping.

Figure 5: Current Metacritic Interface for User Search and Recommendations

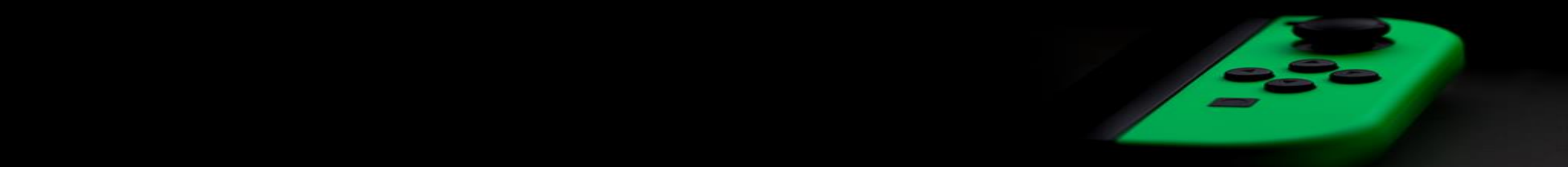
Attribute specific sentiment scoring

As previously mentioned, the core objective of the project is to provide Metacritic readers with a deeper understanding of the different components of games through attribute specific sentiment scoring. In other words, each game on the platform would be rated on more detailed attributes that would allow users to make better informed purchasing decisions based on their gaming preferences.

The generated topic-to-word mapping identified the following 15 relevant attributes: tone, strategy-based gameplay, game design, difficulty, skill-based gameplay, enjoyment, luck-based gameplay, world building, visuals, technical performance, innovative, playthrough time, value, narrative, multiplayer, and soundtrack (cf. Appendix C).

We then took the following approach to generate the attribute specific sentiment scores for each game. For each review snippet, we first identified the words from the topic-to-word mapping. After identifying those words, we performed sentiment analysis using VADER on their neighbouring words (5-grams) to identify the sentiment given by the review snippets to those specific words. After computing the sentiment scores for each of those words, the topic-to-word mapping was used to extract the corresponding attributes. The attributes would thus be associated with the word-specific sentiment scores generated. If an attribute was mentioned multiple times in a review snippet, the average sentiment score was computed for that attribute. This process allowed us to score each review on different game attributes. The average sentiment score per attribute was then computed for each game to get the attribute specific sentiment score per game.

A positive score for an attribute would indicate to Metacritic users that critic reviewers are positively judging the game on that specific attribute. On the other hand, a negative score for an attribute would indicate the opposite. This tool, if implemented correctly, could become a rich



source of information for consumers seeking to purchase games while keeping their time researching low.

Table 1: Average score per game per attribute

game_name	metascore	tone	strategy based gameplay	game design	difficulty	skill based gameplay	enjoyment	luck based gameplay	world building	visuals	technical performance	innovative	play through time	value	narrative	multiplayer	sound track
Disco Elysium: The Final Cut	97.27	0	0	0	0	0	0	0	-0.25	0	0	0	0	0	0	0	0
Final Fantasy XIV: Endwalker	91.96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Forza Horizon 5	91.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
...																	
Of Bird and Cage	43.85	0	0	1	0	0	0	0	0	0	0.34	0.68	0	0	0	0	0
Balan Wonderworld	39.73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
eFootball 2022	24.00	0	0	0	0	0	0	0	0	0	0	0	0	0.29	0	0	0

Metascore prediction modeling

To validate the value of the insights provided by the attribute-specific sentiment scores per game, we have decided to run a multivariate linear regression model. Specifically, we have regressed Metascore –provided by Metacritic– onto our 15-ranking metrics. The data was standardized as the Metascore and sentiment score scales are different. The following figure summarizes the output of the regression.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              metascore   R-squared:                       0.080
Model:                            OLS   Adj. R-squared:                  0.035
Method:                 Least Squares   F-statistic:                     1.777
Date:                Sun, 13 Feb 2022   Prob (F-statistic):             0.0371
Time:                        20:10:39   Log-Likelihood:                -442.03
No. Observations:                 321   AIC:                             916.1
Df Residuals:                     305   BIC:                             976.4
Df Model:                          15
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
const                   -1.336e-16      0.055  -2.43e-15      1.000      -0.108       0.108
tone                       -0.0331      0.057     -0.584      0.560      -0.145       0.079
strategy based gameplay     0.1116      0.062      1.815      0.070      -0.009       0.233
game design                 0.0559      0.058      0.967      0.334      -0.058       0.170
difficulty                 -0.0133      0.057     -0.234      0.815      -0.125       0.099
skill based gameplay        0.0365      0.058      0.626      0.532      -0.078       0.151
enjoyment                  -0.0780      0.058     -1.335      0.183      -0.193       0.037
luck based gameplay         0.0360      0.056      0.645      0.519      -0.074       0.146
world building             -0.0064      0.058     -0.110      0.913      -0.121       0.108
visuals                    -0.0302      0.056     -0.535      0.593      -0.141       0.081
technical performance      -0.1515      0.057     -2.673      0.008      -0.263      -0.040
innovative                 -0.1008      0.058     -1.753      0.081      -0.214       0.012
playthrough time            0.0054      0.057      0.096      0.924      -0.106       0.117
value                      -0.0773      0.057     -1.354      0.177      -0.190       0.035
narrative                   0.0438      0.056      0.783      0.434      -0.066       0.154
multiplayer                -0.0474      0.056     -0.842      0.401      -0.158       0.063
==============================================================================
Omnibus:                       80.165   Durbin-Watson:                   0.193
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              235.351
Skew:                          -1.120   Prob(JB):                     7.84e-52
Kurtosis:                       6.546   Cond. No.                         1.77
==============================================================================
```

Figure 1: Model output and description of a multivariate linear regression model

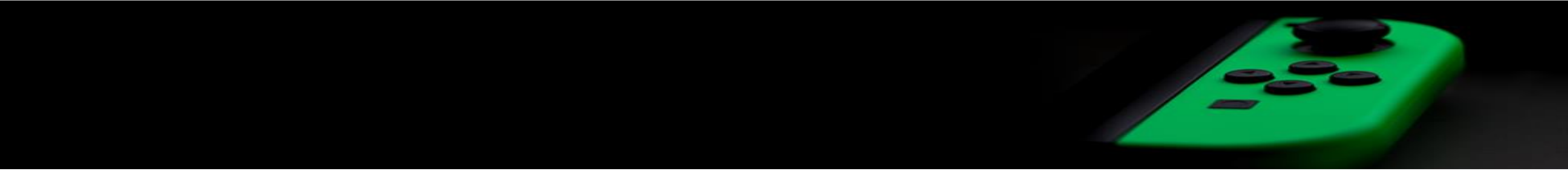
As shown, the R squared of the model is low at a value of 8.0%. This means that only 8.0% of the variability in the Metascore can be explained by our 15 ranking scores. Our attribute-specific sentiment scores are struggling to capture the variability of the average game score provided by critic reviewers. We have identified two reasons that could explain this result.

First, during the pre-processing stage, we have noticed that VADER failed multiple times at identifying the true sentiment of reviews. Since VADER was used to compute our attribute specific sentiment scores, one could argue that the model's poor performance could be attributed to that. Another reason that could explain our model's poor performance would be that we have performed our text analysis on review snippets and not on full reviews. Performing sentiment analysis on review snippets may fail to capture the true sentiment of critic reviewers for a given game. Running the same analysis on full reviews using another tool other than VADER might have led to more accurate scores.

Although the R-squared of the model is low, its p-value proved to be statistically significant at the 5% level with a value of 3.71%. This implies that the model provides value despite its low R-squared. In other words, we might have missed other game attributes that could have better captured the variability of Metascore. Similarly, we might have failed to build a comprehensive topic-to-word mapping by omitting other relevant words for each attribute.

Additionally, three features stand out by being statistically significant at the 10% level. These three features are strategy-based gameplay (7.0%), innovative (8.0%) and technical performance (0.81%). Looking at the corresponding coefficients we can infer the following interpretations:

1. **Strategy-based gameplay:** Increasing the strategy-based gameplay sentiment score of a game by one standard deviation, increases the metascore by 0.1096 standard deviations. In



other words, the more a game is positively seen as being strategy focused, the more likely it is given a higher score by critic reviewers.

2. **Innovative:** Increasing the innovative sentiment score of a game by one standard deviation, decreases the metascore by 0.1014 standard deviations. In other words, the more a game is positively seen as being innovative, the more likely the game developers have taken risks that may not appeal to everyone.
3. **Technical performance:** increasing the technical performance sentiment score of a game by one standard deviation, decreases the metascore by 0.1547 standard deviations. In other words, the more a game is seen as having less technical issues, the less likely it is given a higher score by critic reviewers. This result is counterintuitive and can again be explained by VADER's poor performance. For example, the n-gram snippet "selfdoubt big issue Like character" was given a sentiment score of 0.3612 for this attribute even though there are no clear mentions of technical issues.

To further enhance our predictive analysis, we have trained a non-linear model. More specifically we trained a gradient boosting regression model on our data which outputs the feature importance score of each of our variables. The R-squared of the model came out to be 54.35% which is a major improvement from the previous model. Still, the performance could be increased by using another sentiment analysis tool and identifying other informative game attributes.

The following table summarizes the top 5 most important attributes for Metacritic score prediction.

	Feature Importance
value	0.144077
game design	0.132045
skill based gameplay	0.102974
strategy based gameplay	0.098395
playthrough time	0.096400

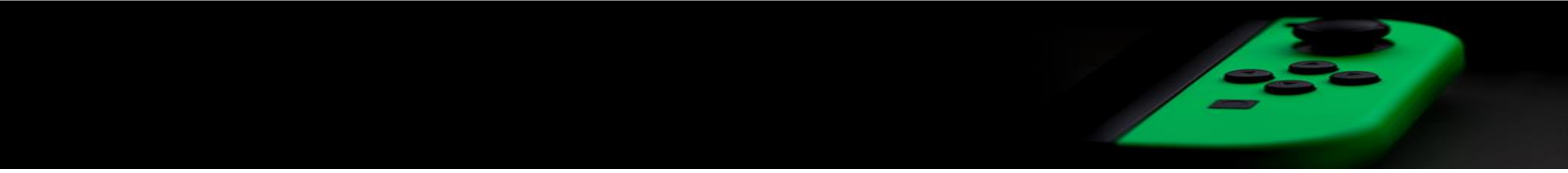
Figure 2: Top 5 attributes for Metacritic score prediction

As we can see, value for money, game design, strategy-based gameplay, skill-based gameplay and playthrough time are very important for Metascore prediction and are thus the ones a game studio could focus on if they wanted to improve the critical reception of the game.

Game Clustering and Recommendations for Users

After analyzing the current Metacritic website, we felt that it lacked components that allowed users of the site to search for games based on attributes and topics that are most important to them (See Appendix B for current user interface). The current website only allows a user to search by game name and by game genre. To enhance user experience, we created two methods of recommender systems that we believe can be implemented on Metacritic's website.

The first method incorporates the user's attribute/key word search input and provides the top 10 most similar games and their reviews that matched the closest to the search. This approach uses count vectorizer on the processed reviews filtered to include reviews with positive sentiment analysis. Lastly, cosine similarity between the vectorized reviews and the user's input was used to



identify the most similar reviews. The output allows the user to view the game name, the score, the author of the review, and the review itself (see Figure 3).

Attribute search: beautiful game design

	game_name	score	author	date	summary
515	Inscryption	100	Gaming Nexus	Oct 18, 2021	Go into Inscryption as unspoiled as possible, ...
323	Mini Motorways	90	IGN Japan	Aug 30, 2021	Similar to Dinosaur Polo Club's previous game ...
1761	Gloomhaven	90	Games.cz	Nov 30, 2021	The best-reviewed board game in the world gets...
473	Death's Door	90	Digitally Downloaded	Jul 20, 2021	Death's Door is a tremendously well-designed g...
2553	Sable	90	But Why Tho?	Sep 22, 2021	Playing Sable very well may be as close as one...
2555	Sable	90	Checkpoint Gaming	Sep 22, 2021	The occasional bug and missing stamina upgrade...
745	Little Nightmares II	88	Atomix	Feb 9, 2021	Little Nightmares 2 is a fantastic sequel that...
2815	The Wild At Heart	80	God is a Geek	May 20, 2021	The Wild at Heart is a beautiful game, with so...
2522	Jurassic World Evolution 2	60	Games.cz	Jan 13, 2022	Building your own Dino Park may be more fun th...
3961	Mutropolis	60	Digital Chumps	Feb 26, 2021	Overall, Metropolis has the bones to be a grea...

Figure 3: User attribute search for game recommendations

The second recommender system we created involves cluster analysis on positive sentiment reviews based on topic groupings previously defined in the topic modeling section. The goal of this cluster analysis will be to provide users another way to get game recommendations based on topics, with a similar presentation to the current game genre recommendation in appendix B.

For the analysis, we applied count vectorizer on lemmatized reviews with stop words removed to get the frequencies of the top 500 features. We chose count vectorizer because it made it easier to sum aggregate word attribute frequencies according to their respective topic grouping. These topic frequencies were then sum aggregated by video game name to get the total frequency of each topic for each video game. Video game sentiment and score were aggregated by the mean value.

We input the aggregated data set into a Kmeans clustering model using the elbow method to determine the optimal number of clusters (three clusters). The following are the summary statistics and the top 5 topics that are closest to each cluster centroid:

Table 2: Summary statistics for each cluster

	Cluster 1	Cluster 2	Cluster 3
Number of Games in the Cluster	*267*	*53*	*1*
Average Metascore	*79*	*74*	*83*
Average Sentiment Value	*0.75*	*0.73*	*0.76*

Table 3: Top 5 topics for each cluster

Cluster 1	Cluster 2	Cluster 3
Tone	*Tone*	*Value*
Skill based gameplay	*Skill based gameplay*	*Tone*
World building	*World building*	*Skill based gameplay*
Soundtrack	*Soundtrack*	*World building*
Luck based gameplay	*Innovative*	*Difficulty*

The first cluster contains the largest grouping of video games with an average score of 79. Its main characteristics are video games that focus on tone, gameplay based on a user's skill and luck, a well-developed world design, and an engaging soundtrack. The second cluster is very similar, with the difference being a larger focus on innovation. The third cluster contains only one video game and is characterized as high value with a positive tone, and reliance on competent and challenging skill-based game play and world building. Although our dataset contains reviews for 321 video games, we anticipate that the third cluster will contain more video games once the topic clustering analysis is implemented on all video games on the Metacritic website. When observing these clusters on an MDS plot based on cosine similarity, we can visually see the differences between cluster 1 (green) and cluster 3 (orange).

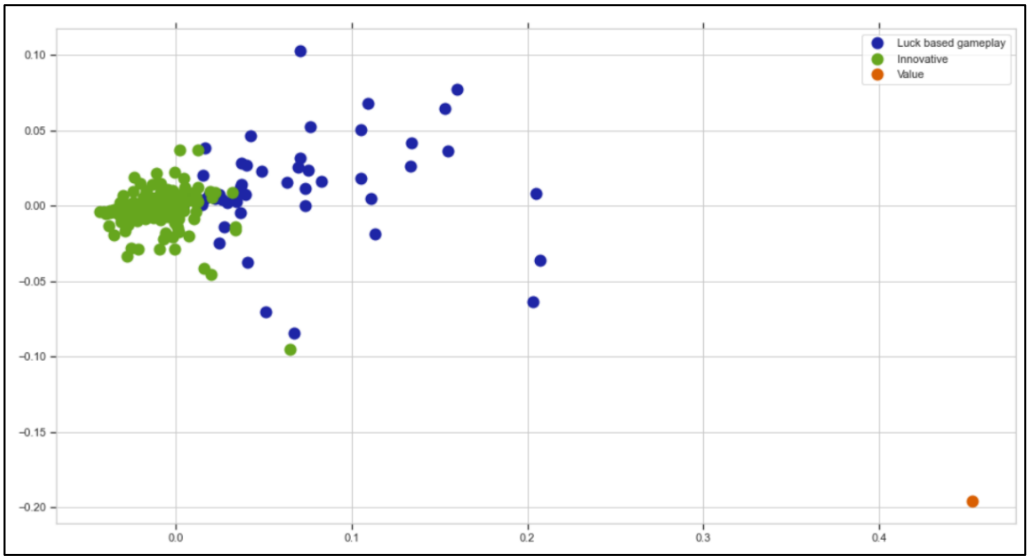


Figure 4: MDS plot of game clusters

Table 4: Top scoring video games in each cluster

Cluster 1	Cluster 2	Cluster 3
Psychonauts 2	*Disco Elysium: The Final Cut*	*Age of Empires IV*
Hitman 3	*Final Fantasy XIV: Endwalker*	
Nioh 2: The Complete Edition	*Forza Horizon 5*	
Inscryption	*Chicory: A Colorful Tale*	
ENDER LILIES: Quietus of the Knights	*It Takes Two*	

Time Series Analysis

Another potential feature that could be useful for the gaming community especially the game developers would be adding a time-dimension to the sentiment analysis. Such a time-series analysis would allow game developers to quickly skim through the critic reviews and understand the weaknesses of the previous game releases and therefore, focus on improvement areas for future game patches and launches. This could potentially be a source of "voice of the user" and help them reduce the risk of failed new game release. The idea was crafted after acquiring the information that an extremely popular game - Grand Theft Auto (GTA) will be launching a new release after an 8-year gap. A feature that quickly helps game developer of GTA to analyse the potential weaknesses of the previous releases would help make the latest launch a success.

For the proof of concept, we scraped all the critic reviews of a total of 12 releases of Grand Theft Auto from 2002-2012 from the Metacritic website. The process of data wrangling and feature extraction was same as earlier and a sentiment analysis was performed on the game attributes for each of the releases. This processing resulted in a matrix of game releases and the critic's overall score and sentiments for each of the game series launched in the given 10 years' period. Since there were a few years like 2009 where more than one series was launched, we aggregated the sentiment score over the date rather than the release title to make it easier for the game developers to analyse the change in sentiments over the years. For easy comparison with the critics score (0-100) on the plots, the sentiment score was multiplied by 1000.

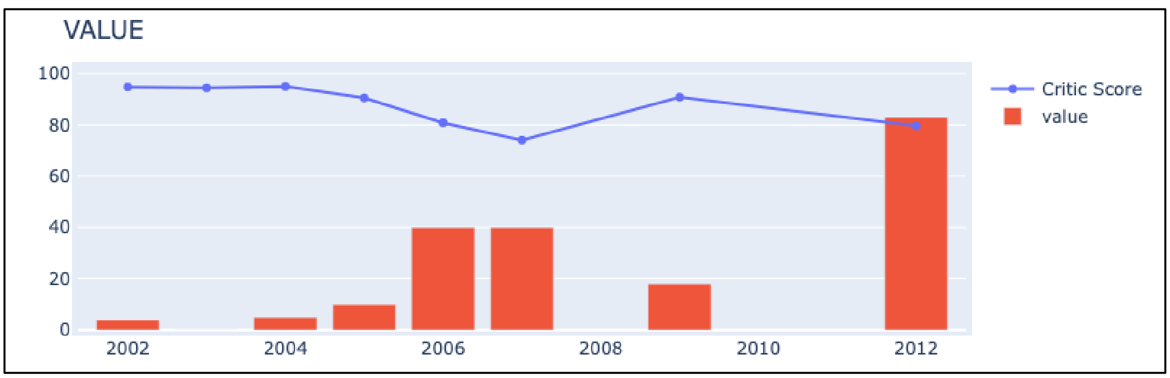
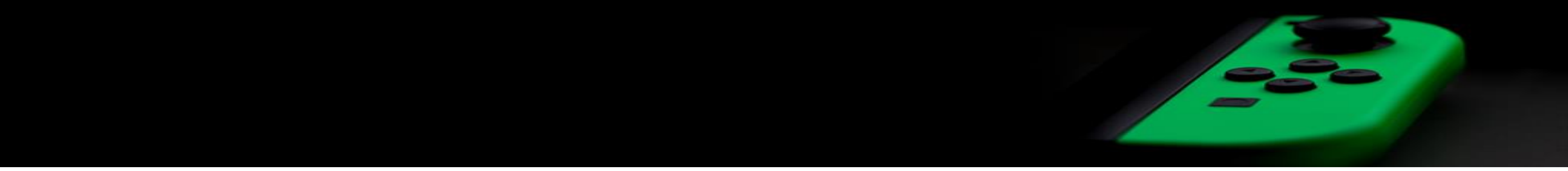


Figure 5. Time series plot of sentiment score of Value attribute (scaled to 1000)

Glancing over the visual plots of the sentiment scores of each game attributes for GTA, we can see that the game has improved its performance across all attributes – especially the value of the game. This shows that the critics associate GTA's value with a high positive sentiment and it has improved a lot in 2012's release. We can also see from the plots that while soundtrack used to be a topic of discussion for critics in early years, most critics now rarely use it as an attribute to judge



the game quality. For GTA, game design seems to be one of top criteria for critics' reviews and good for the developers that critics have good things to say about the design of the game.

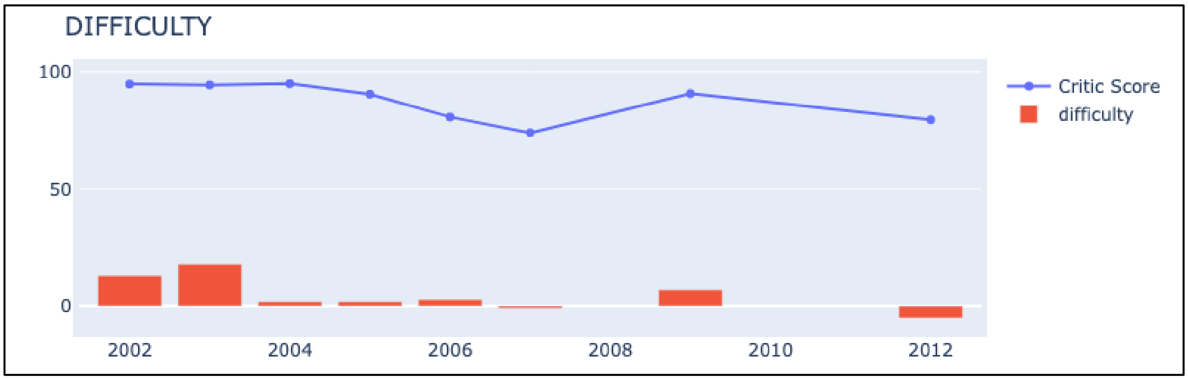


Figure 6: Sentiment score of Difficulty attribute (scaled to 1000)

Focusing on the areas of improvements, the plots show a fall in the sentiment scores for the difficulty of the game i.e., either the game is too difficult, or the game is too easy compared to previous releases and this could be an interesting area to find a balance in difficulty level for the next release.

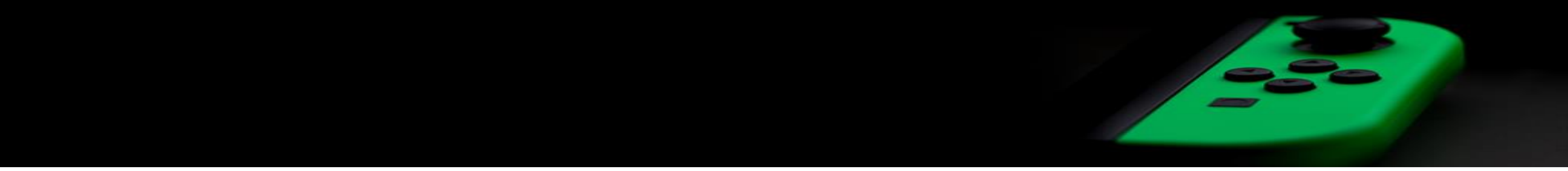
This feature of time series analysis therefore allows the game developers to potentially save resources in terms of surveying user base to find the gaps in the game launches and quickly zoom in on the weaknesses. An expansion of this feature worth exploration would be to not only analyse the critics reviews but also the difference in the critics and user's sentiments if any across all the game attributes and a general trend in the sentiments of users across different genres, so the game developers have an easy access to the dynamically changing user perception & requirements of a game.

Conclusion

Based on our analysis, we believe that the implementation of an automated game attribute scoring feature for Metacritic games can add significant value to the Metacritic user experience. This is especially true given the potential to implement a content-based recommendation system that can incorporate the similarity of games based on identified strengths and weaknesses. These recommendations can guide user purchase decisions more effectively and potentially expose users to less popular games that better fit their preferences.

When evaluating the value of the insights using a predictive model, we found that the attribute scores/ metascore relationship is more accurately modelled using a non-linear method such as GBT which significantly outperformed linear models. To further improve the quality of the insights gained from these features we recommend expanding the reviews considered by including user reviews available on the site as well as using a more advanced sentiment analysis model such as GPT3's sentiment analyzer to improve accuracy of sentiment scores. We also see applications of this analysis for video game publishers as we were able to determine which attributes tend to impact reception based on a simple feature importance analysis.

Finally, we demonstrated a potential application of the newly acquired scores in a time series analysis of the GTA franchise. This analysis provided insight into the evolution of the GTA brand based on its perceived strengths and weaknesses, valuable information for the game publishers as they begin to kick-off development on the next title.



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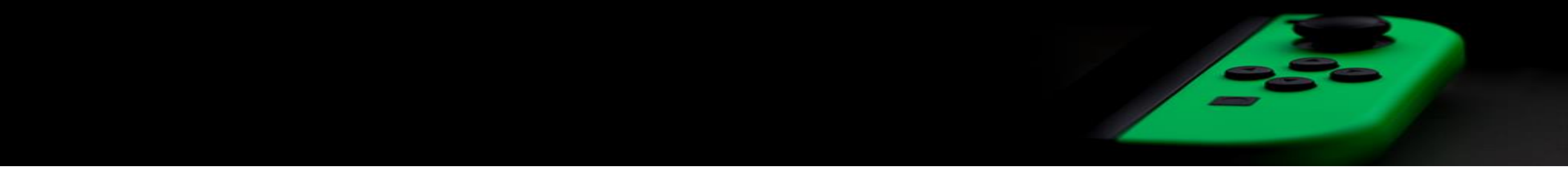
Appendix A

Table 5: Data Description (Games)

Games	
Id	*Unique identifier for each game title*
Name	*Game title*
Developer	*Game developer*
Release Date	*Date game was published*
Metascore	*Aggregate review score from all captured critic reviews*
Review Platform	*Gaming platform on which review was conducted*
Other Platforms	*Gaming platforms where game is available not including the review platform*
Genres	*Game genre(s)*
Online Player Number	*Number of online players (if applicable)*
Rating	*Game maturity rating*

Table 6: Data Description (Reviews)

Reviews	
Game Id	*Unique identifier for each game title*
Game Name	*Game title*
Score	*Review score provided by reviewer*
Author	*Reviewer name or publication name*
Date	*Date review was published*
Summary	*Blurb extracted from full article and displayed on Metacritic site*



Appendix B – Current User Interface for User Recommendations

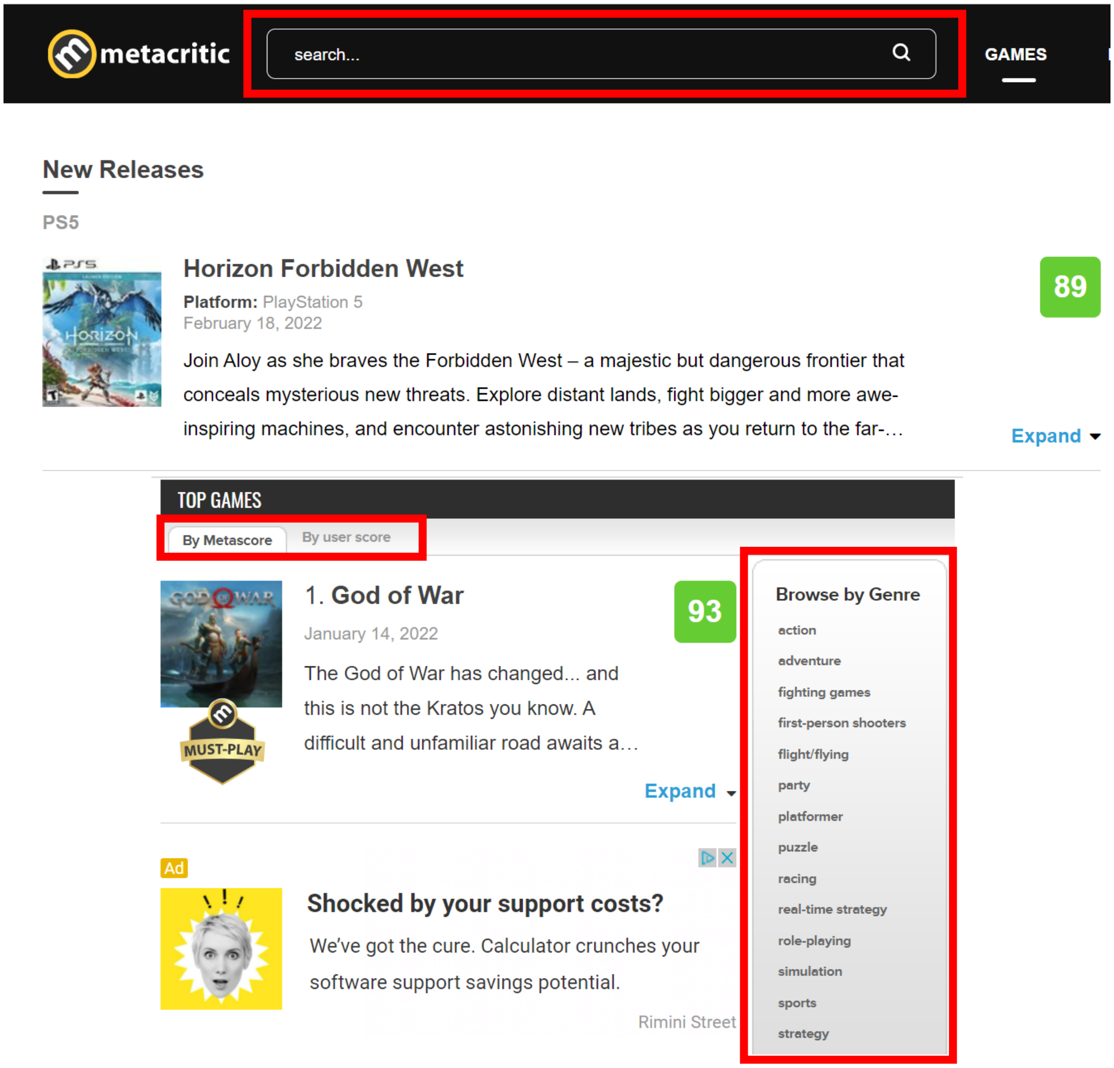


Figure 5: Current Metacritic Interface for User Search and Recommendations

Appendix C – List of game attributes identified

Table 7: List of game attributes identified in Metacritic reviews

Attribute	Related Words	Example
game design	*18*	*gameplay*
innovative	*13*	*inspiration*
enjoyment	*11*	*fun*
tone	*11*	*sad*
technical performance	*8*	*issue*
skill based gameplay	*7*	*shooter*
narrative	*6*	*storyline*
world building	*6*	*openworld*
visuals	*6*	*aesthetic*
strategy based gameplay	*6*	*strategy*
playthrough time	*6*	*time*
difficulty	*4*	*challenge*
value	*2*	*money*
multiplayer	*2*	*coop*
soundtrack	*1*	*music*

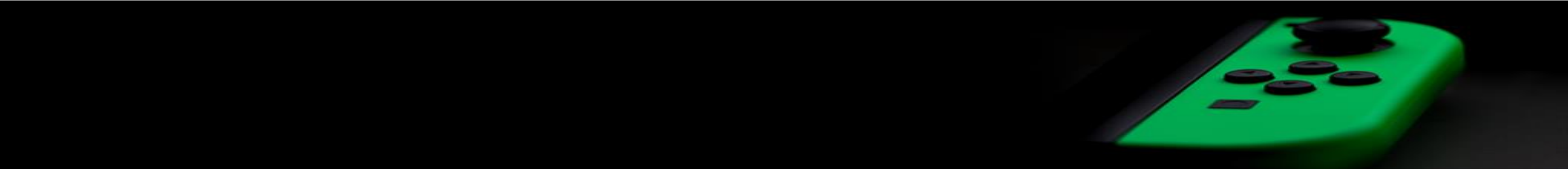


Table 8: Derived attribute to word mapping

Word	Group	Word	Group	Word	Group
easily	difficulty	franchise	innovative	entertaining	tone
hard	difficulty	age	innovative	cute	tone
survival	difficulty	fascinating	innovative	cry	tone
challenging	difficulty	first	innovative	happy	tone
fan	enjoyment	chance	luck based gameplay	classic	tone
enjoy	enjoyment	multiplayer	multiplayer	refreshing	tone
exciting	enjoyment	coop	multiplayer	pleasant	tone
boring	enjoyment	narrative	narrative	taste	tone
fun	enjoyment	character	narrative	niche	tone
pleasure	enjoyment	storyline	narrative	nice	tone
satisfy	enjoyment	story	narrative	money	value
interested	enjoyment	hero	narrative	worth	value
attention	enjoyment	life	narrative	artistic	visuals
effect	enjoyment	hour	playthrough time	animation	visuals
play	enjoyment	pace	playthrough time	aesthetic	visuals
mission	game design	playthrough	playthrough time	visuals	visuals
campaign	game design	complete	playthrough time	pretty	visuals
flaw	game design	run	playthrough time	gorgeous	visuals
system	game design	time	playthrough time	openworld	world building
element	game design	battle	skill based gameplay	world	world building
experience	game design	sniper	skill based gameplay	exploration	world building
mode	game design	combat	skill based gameplay	lost	world building
vr	game design	shooter	skill based gameplay	space	world building
gameplay	game design	action	skill based gameplay	fantasy	world building
design	game design	fighting	skill based gameplay		
adventure	game design	fight	skill based gameplay		
mechanic	game design	music	sound track		
single	game design	strategy	strategy based gameplay		
roleplaying	game design	turnbased	strategy based gameplay		
jrpg	game design	puzzle	strategy based gameplay		
simulator	game design	tactical	strategy based gameplay		
genre	game design	management	strategy based gameplay		
interaction	game design	decision	strategy based gameplay		
interesting	innovative	technical	technical performance		
intriguing	innovative	issue	technical performance		
inspiration	innovative	expected	technical performance		
traditional	innovative	problem	technical performance		
genius	innovative	rough	technical performance		
surprising	innovative	remaster	technical performance		
added	innovative	polish	technical performance		
series	innovative	pc	technical performance		
entry	innovative	dark	tone		

Fig 7: World cloud of the topic model output