Video Game Analysis: Trends and Insights

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Abstract. This project examines patterns and trends within the video game sector, utilizing information from diverse sources to gain insights on game popularity, sales statistics, player demographics, reviews analysis and genre success. The study's goal is to pinpoint crucial factors that impact the success of video games and to represent these patterns through graphs and charts. This report offers a thorough summary of the video game market's current condition by gathering and organizing pertinent data, facilitating well-informed decision-making for stakeholders.

INTRODUCTION

The video game industry has quickly transformed from a specialized market to a worldwide force, propelled by technological progress and a variety of player demographics. This project examines patterns in the video game industry, with a specific emphasis on sales figures, genre trends, and player involvement.

Our goal is to discover important insights for developers and marketers by analyzing data from different sources like sales numbers and critical reviews. What types of genres are the most prevalent in the market? What is the relationship between game ratings and sales? By carefully gathering, scrubbing, and presenting data, this document offers a thorough examination of the gaming industry, emphasizing the correlation between consumer actions and market patterns. It is essential to grasp these dynamics in order to successfully navigate the future of the industry.

DATA COLLECTION/PREPARATION

This section discusses the procedure and measures we choose to collect data and the sources of our database. This section also details the issues and errors while preparing the data for visualization process.

Data Sources

- 1. SteamDB: Sales and user reviews for PC games.
- 2. API Access: The data utilized in this work comes directly from Steam via an API. There are three main API calls utilized to collect the data:
 - https://api.steampowered.com/ISteamApps/GetAppList/v2/. This is used to acquire all Steam app IDs.
 - https://store.steampowered.com/api/appdetails?appids=<APPID>, where APPID is the steam application ID number. This is used to to collect details about a single Steam application.
 - https://store.steampowered.com/appreviews/<APPID>?json=1&num_per_page=100&cursor=<CUR>
 &filter=recent&purchase_type=all, where CUR is a string representing the next page of reviews if
 there are multiple pages.

Fig.1 is the image of the json file of the collected data.



FIGURE 1. Image of json file of data

Data Schema

Here is the schema of the final database we collected to make sure o the structure of the dataset.

Fig.2 Below shows the clear schema of the database.

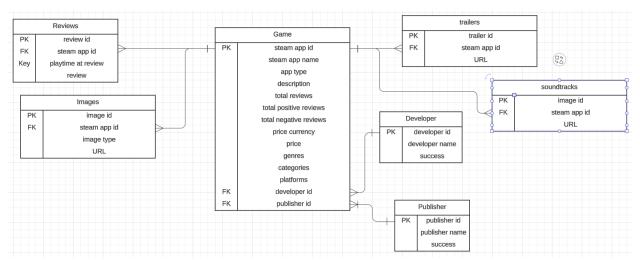


FIGURE 2. Data Schema

Fig.3 shows the exact data file we collected.

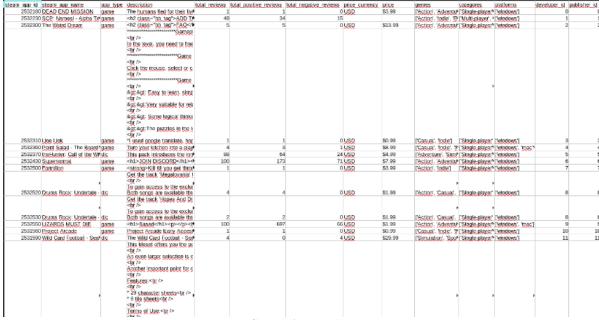


FIGURE 3. Data file

Data Formatting

After collection, the data was organized into structured formats, primarily using CSV files. Each dataset included columns for game titles, release dates, sales figures, ratings, genres, and player demographics.

Data Integration

We tried to integrate multiple datasets but couldn't manage to do it at this point of the project timeline. But sure we were going to merged using common identifiers (e.g., game titles) to create a comprehensive dataset that includes sales, ratings, and demographic information.

Data Cleaning

Handling Missing Values: Utilized imputation methods for handling missing numerical data and excluded rows with significant missing values.

Removing redundants:

Recognized and eliminated repeated entries in order to maintain data accuracy.

Standardizing Formats:

Guaranteed uniformity across date formats, genre names, and other categories.

Outlier Detection:

Identified outliers in sales data and ratings using Z-scores and IQR methods, and assessed their impact on overall analysis.

Tools Used

- Pandas: Used for data cleaning and manipulation in Python.
- NumPy is used for performing numerical computations and managing missing data.

Data Visualization

Plots used:

- 1. Bar Charts
- 2. Line Graphs
- 3. Heatmaps
- 4. Pie Charts
- 5. Bubble graph
- 6. Scatter plot

Visualizations:

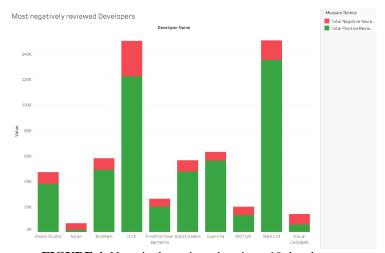


FIGURE 4. Negatively reviewed reviews 10 developers

The Fig.4 below show initial insight into the data. Below each is a caption describing them. The x axis is the top 10 most negatively review game developers and y axis is the total positive and negative reviews. We can see that rare 1td and DICE are the two most negatively reviewed game developers and that most developers have almost nearly equal positive reviews as well.

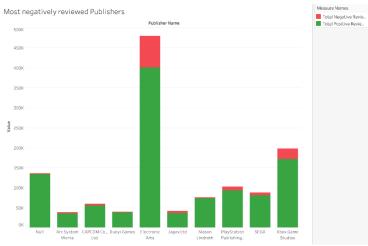


FIGURE 5. Most negatively reviewed 10 publishers

This graph in Fig.5 displays the top 10 most negatively reviewed game publishers and the number of positive (green) reviews and negative (red) reviews they get. We can observe that electronic arts has the most negative reviews as well, and that most of these publishers have comparable number of positive reviews to the negative reviews. Implying that people tend to have mixed opinions on game publisher games.

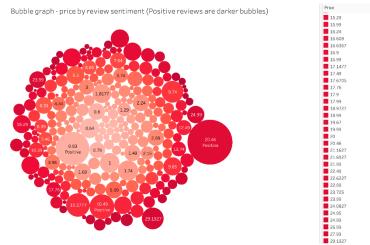


FIGURE 6. price vs reviews

The bubble plot Fig.6 shows the price vs review sentiment (which is the ratio of positive and negative reviews). The bubble size denotes the value of review sentiment (larger bubble implies positive review). While the colour denotes the price, more red implies more pricey game. We can observe that more pricey games tend to have more positive review sentiment, and vice versa. Which can be confirmed as less pricey games tend to be made by cheaper indie game developers who cannot make the best of games.

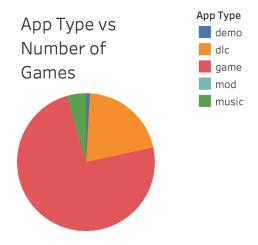


FIGURE 7. Game types

The pie chart Fig.7 shows the app types like game, demo, dlc, etc vs the total number of games. We can observe that the game app type is most common followed by dlc and music.

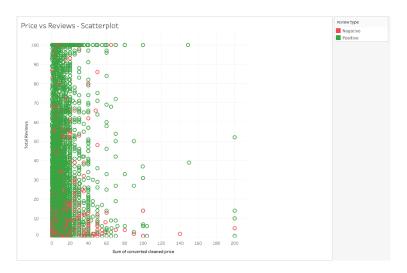


FIGURE 8. Price vs Reviews

The graph in Fig.8 total number of reviews for each price range of each game. Red are net negatively reviewed games and green and net positively reviewed games. We have removed outliers to make the graph more digestible. We can see that most games are positively reviewed, only a few are negatively reviewed. This mean the data is more skewed towards positive reviews. We can also observe that the data is more concentrated towards the left end, meaning games tend to be less pricey. But on the y axis the total reviews are quite equally spread apart, meaning there is no visible trend with games and number of reviews.

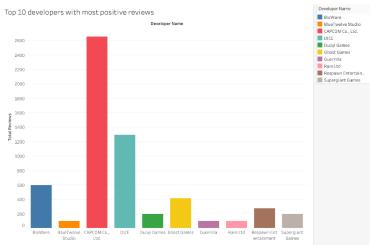


FIGURE 9. Most positively reviewed 10 developers

In above graph $Fig.9 \ X$ axis is the top 10 game developers based on positive user reviews. Y axis is the total reviews received by each developer. We can see that capcom co has the highest reviews and is followed by dice, but there is a huge difference between the two. We can see that BioWare is the most positively reviewed developer.

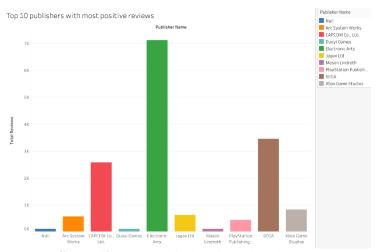


FIGURE 10. Most positively reviewed 10 developers

Above plot Fig.10 has X axis as the names of the top 10 publisher names, which were found using the most positive reviews. Y axis has the total number of reviews. This graph shows the top 10 publisher names, and that electronic arts has the highest number of reviews, and arc system works has the highest number of positive reviews.

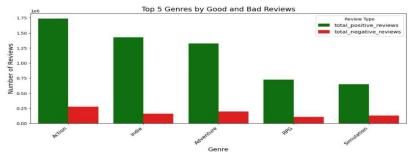


FIGURE 11. Genre analysis (Good vs Bad reviews

Fig.11 X axis has the names of the top 5 game genres, which were found using the most positive reviews. Y axis has the total number of reviews. This graph shows the top 5 genre names, and that action is the most liked game genre and these have very little negative reviews.

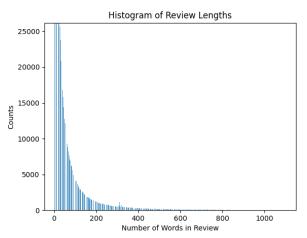


FIGURE 12. Number of words in reviews

The x axis in Fig.12 shows the number of words in a review and the y axis shows how many reviews had that many words. Perhaps unsurprisingly, words with fewer words are more common while reviews with more words are less common.

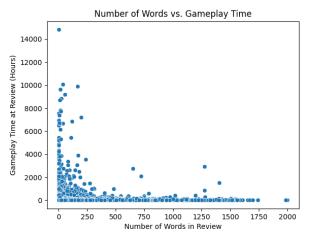


FIGURE 13. Number of words vs Gametime

The Fig.13 shows number of words in a review plottted against how long someone had played the game before leaving a review. Intuitively, one may believe that longer, more indepth reviews would come from people who have played the game longer. However, this is not the case. Longer reviews typically come from people with a shorter amount of playtime. This could present interesting ideas for analysis later on.

MODEL IMPLEMENTATION

Variables in the dataset are, reviews, price, developer, publisher, genre, currency, platforms, images, number of reviews, positive reviews, negative reviews, brightness, contrast, saturation and hue.

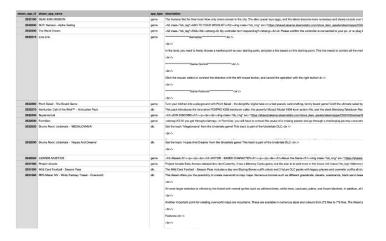
1. CLIP MODEL: CLIP is a multimodal model, proposed by OpenAI, that aligns textual and image embeddings into a joint space. It was trained to predict which caption fits best for an image among candidates, allowing it to learn associations of visual and textual data. Trained on diverse image-text pairs, CLIP can execute tasks such as image classification, retrieval, and zero-shot learning without fine-tuning specifically for individual tasks. Using a dual encoder architecture, it processes images through a vision model-e.g., ResNet or ViT-and processes text using a transformer to produce embeddings to be compared. Such flexibility and generalization make CLIP a very powerful model for different visual-linguistic applications.

WHY WE USED IT:

We utilized the CLIP model in our project to examine and find associations between game images and their textual descriptions. The ability of this model to create a common embedding space for text and images allowed us to efficiently perform tasks like image classification and retrieval, helping uncover patterns, understand context, and improve insight into the relationships between visuals and game descriptions.

DATA CLEANING:

How data looked before cleaning:



After cleaning:

	steam_app_id	cleaned_description
22135	1097960	br game party skills unique team idle gems cla
22714	1084860	br risk system deluxe content original light e
14642	1266070	stage healthy box vr fitness game people willi
21109	1120461	lord zedd character power rangers battle grid
1045	2484670	chess game games remix world rules new play sh
20667	1130990	br roman romans evil britons level welcome sea
2714	2417700	unique steam extras strong malice platformer a
16973	1212690	borg instructors mountain faulty apprentice dl
5312	2325880	game heroes players battle deck zodiac abiliti
10495	1375270	maze steam extras shadow reborn ego shape expe
9939	1389830	electronic components power steam extras robot
15236	1254700	format
2533	2425050	steam extras person night fang mysterious new
14438	1270620	chemistry steam extras molecules simulation re
7047	2264940	dlc valentine xi churchill
14618	1266440	br treatment dungeon health way tests obstacle
13771	1285610	people horror game city person thrill feelings
24033	731180	coffee run game upgrade graphics ui gameplay c
4059	2370540	love note steam extras notebook japanese roman
7346	2254780	steam game mini keys games points characters k
23391	1070400	br artefacts player mode maldrin journey game
20063	1145360	supergiant god like steam extras strong underw
15538	1246390	br steve human silent hill game average day in
20807	1127620	picture bylo quick horror game experience back
10436	1376470	bear ears cave lantern footsteps hunted large
18571	1178870	br characters battlers rpg maker hero bust pac
18092	1189060	steam extras game explosions floor weapons str
7819	2239140	grappling players physics hook movement active
20363	1138260	steam extras level action strategy battlefield

This would serve to clean game descriptions of noise like irrelevant words and characters, hence making the text data concise and meaningful. The preprocessing step helps in improving the quality of the textual embeddings that are generated by the CLIP model, therefore improving its ability to relate game descriptions with their corresponding images accurately. Cleaned data reduces computational complexity and improves overall model performance.

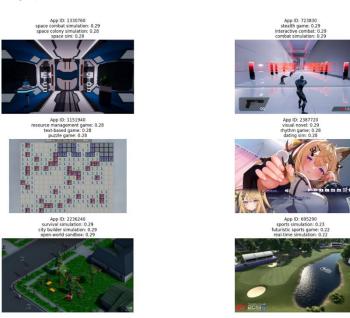
Cleaning was also done for image dataset, such as removing 404 error URLs and only filtering screenshots for more consistent training.

MODEL EVALUATION (using similarity scores):

```
Similarity scores:
[[0.1638 0.2218 0.1312 ... 0.169 0.1782 0.1259]
[0.1913 0.2017 0.1605 ... 0.1886 0.2017 0.1562]
[0.22 0.232 0.2188 ... 0.2515 0.23 0.208]
...
[0.2034 0.251 0.2646 ... 0.2292 0.2242 0.2021]
[0.2034 0.251 0.2646 ... 0.2292 0.2242 0.2021]
[0.2034 0.251 0.2646 ... 0.2292 0.2242 0.2021]
```

The similarity scores indicate how well text embeddings (e.g., game descriptions) align with image embeddings in the CLIP model. Each value represents the similarity between a text-image pair where higher scores indicate stronger associations. Rows correspond to text embeddings, columns correspond to image embeddings, and together this allows for an evaluation of CLIP's effectiveness at multimodal alignment. The scores are cosine similarity, between 0 and 1. Since we are finding custom descriptions for completely new images, even a score above 0.2 is good.

OUTPUT:





The CLIP is model is very effective in describing what each game image is. In a matrix of 10 images, it was able to correctly describe each image. Thus proving CLIP is a effective image to text model. The examples of results

provided show the capability of the CLIP model in analyzing and describing game screenshots in high detail. For each of the nine game images, CLIP identified relevant tags or genres such as "space combat simulation," "stealth game," "resource management game," and "visual novel," among others. It successfully aligned visual elements from the images with meaningful semantic labels, showcasing its capability to understand and interpret visual data in the gaming context. The CLIP is model is very effective in describing what each game image is. In a matrix of 10 images, it was able to correctly describe each image. Thus proving CLIP is a effective image to text model.

WHAT WE LEARNED:

This functionality has many applications in the analysis of games. CLIP enables automation in categorizing and tagging games with screenshots, reducing human effort and improving scalability for large gaming datasets. This can be useful for game developers and platforms in streamlining their metadata creation processes, therefore making it easier for end-users to discover or search for games. It also improves the quality of the recommendation systems by allowing them to suggest games with appealing visuals or gameplay themes that appeal to the users' likings.

Moreover, the ability of CLIP to extract meaningful insights from images will help in content moderation, ensuring the proper classification of the games. By pairing visual data with descriptive text, CLIP bridges the gap between visual representation and semantic understanding and is a powerful tool for indexing, filtering, and analysis of games efficiently and in a scalable manner.

2. GRADIENT BOOSTING: Gradient Boosting is a powerful machine learning technique that generates models sequentially, each new model correcting errors of the previous ones. A weak learner, usually decision trees, is combined into a strong predictive model through minimizing a loss function. Gradient Boosting has a wide range of applications in regression and classification problems, where it maintains accuracy and flexibility.

WHY WE USED IT:

We applied Gradient Boosting to the image data set for an effective modeling of dependencies between features including brightness, saturation, hue and contrast, impacting the visual characteristics. Its ability to deal with non-linear patterns and emphasize misclassified examples ensures accurate predictions. Gradient Boosting flexibility and robustness make this approach ideal for capturing subtle variations and improvement of image-based classification or regression results in general.

DATA CLEANING:

The dataset we created-

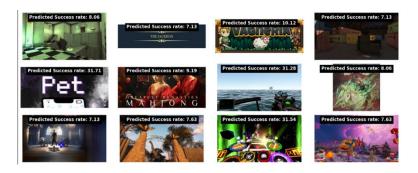


To train the gradient boosting model, we had to create a new dataset from the image URLs, which contained the app ids and image values such as brightness, contrast, saturation and hue. We made this so that we can find patterns in underlying aspects of the images and game success.

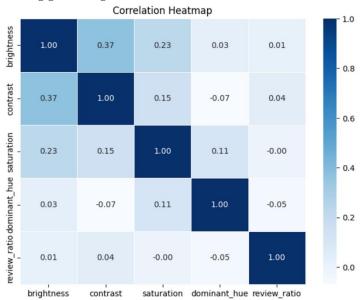
Gradient Boosting Mean Squared Error: 130.68720097122053

We use Mean Squared Error to calculate an average of the squared difference between predicted and actual values. The lower the MSE, the better the accuracy of the model. At a value of 130, the model performance is good, showing that the predictions are relatively near to the actual values; thus, effective learning takes place.

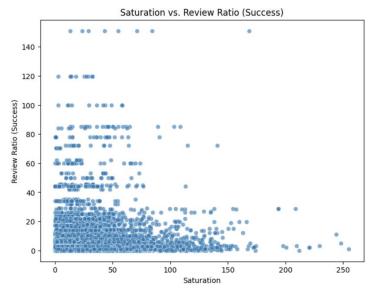
OUTPUT:



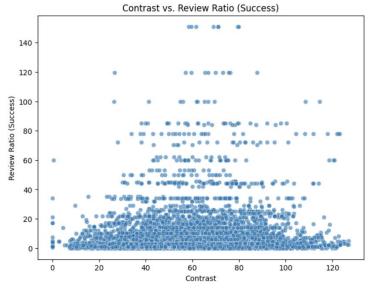
As we can see, the model predicts the success rate, which is the ratio of number of positive reviews to number of negative reviews. It rates higher success rate to games with more interesting game image screenshots and lesser success rates to dull or confusing game image screenshots.



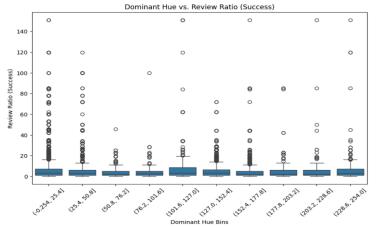
This is a correlation heatmap, showing correlation between various features, as we can see most features are unrelated except contrast and brightness which have some correlation.



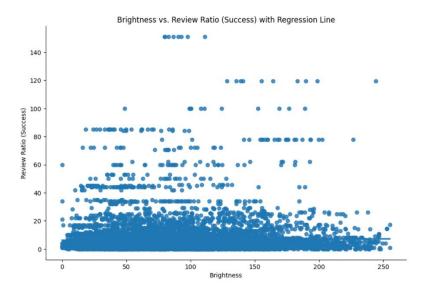
This scatterplot shows the relationship between review ratio (success rate) and saturation of images. As we can see the more saturation implies less review ratio, implying more saturated images might be worse for game success.



This scatterplot is the relation between contrast and success rate. As we can see a contrast between 50 and 80 is the sweet spot. Anything more or less results in less success rate.



This graph is the boxplot relationship between hue and success rate. It shows that all colors have similar success rate and there is no correlation between color/Hue and success of a game. It means that consumers don't prefer one color or the other. Hues between 101-127 (green-yellow) have slightly higher success rate, but nothing can be said with certainty.



This graph shows the relationship between brightness of game images and success rate of those games. As we can see, there is no clear relationship between brightness and game success.

WHAT WE LEARNED:

From this model, we extracted a few important points about how far image features such as brightness, contrast, and saturation will reflect success rates of games through reviews. Thus, the model predicted an optimal range of 50 to 80 for contrast for high success rates, while very low or high values of contrast will negatively affect the review score. Interestingly, saturation is negatively correlated with the success rate, which might indicate that highly saturated images could turn players off. On the other hand, hue did not correlate significantly with success, which would indicate that the consumer's preference is not strongly connected with specific colors. Also, no obvious influence of brightness could be found on the success rate, meaning it's not a determining factor. The model performs well with an MSE of 130, showing that it learns the relationship between the image features and game success quite effectively. This shows the importance of specific image attributes such as contrast in predicting game success.

3. ASSOCIATION RULE MINING:

WHY WE USED IT:

We applied association rule mining to the reviews of the games. We looked at Steam Apps that were classified as a "game" (in other words, we didn't look at DLC or other non-game Steam Apps), and we looked at differences among the top 10 genres. We filtered game reviews by the ratio of positive reviews to negative reviews of a game. If a game had more positive reviews than negative, it was considered a positive and vice versa. We acknowledge that this is not the best method, especially considering Steam reviews are tagged as either positive or negative. A bug in code caused that review tag to not be collected. Grouping reviews by how positively overall the game they are associated with is the best approximation.

ARM requires transaction data. To create the transaction data, we first extracted the necessary reviews according to liked and disliked games and genre. We removed any line break characters, removed capital letters, punctuation, numbers, non-latin characters, duplicate words, and a set of words (such as "game", "ever", "it", "etc") that provide no meaning. Afterwards, we saved the cleaned words as basket data. The two images below show messy data (top) and clean data (right).

DATA PREPROCESSING:

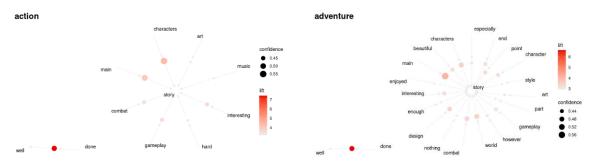
Before:

		ne_at_review (review								
580625 580626	1405180	563 Don't wasto your money/IIIIIIIIII 745/in needs (D15 of work and it think this games deed in the water, Don't Buy IT IIIIIIIIIIII								
00020	1400100	Asian needs Corts on work and in this games dead in the water, contributy in minimin								
80627	1405180	154)A big waist of money they not even working on it should be removed by steam								
80631	1405180	225 This has got to be the west game that I've ever played on Steam. The game itself is very buggy, but the worse part of it is that I paid \$29.99 for this. Anyway, with their recent update to adding multiplayer, they've changed the map, and it's both								
580636	1405180	180 there is very little content in this game. Potential is there, but they are way too slow getting things done. I like playing as a wolf, but there, again, nothing much to do. I wasn't able to rescue animals and then the "eat" key stopped letting me eat								
580638	1405180	this game gigg, work good after 5 min cant do anything								
580643	1405180	447/ 1427/Jt this point game still has too many bugs, sometime's you can craft item's, sometimes you can't. I have never ask for a returnd, but had to on this one.								
580647	1405180	200 Needs a tor of work but it has posterial a new that it has posterial a new that it has posterial a new that it has posterial and the new that posterial and the new								
		Thick the game.								
		At first, your dream has come true - nature around you look realistic and incredibly pretty, aboit a bit repetitive since you will soon discover that the forest you've been placed out in - is some kind of secret cloning research government program of								
		Run forest - RUN								
		And that's exactly what you will be doing for hours, days even - numring around in a forest, like Qygig himself, and no one knows where you get that world class numring power from, because you don't run out of stamina at all. You run like a char								
		So, I run! Now what?								
		If you've managed to figure out where all the gegues are (tab being the most obvious one, with a not so obvious way to get OUT of the tab (invertory) once you click on something there but once you're past that little 200 IQ challenge, then you								
		Wel about that								
		You realized some enough that you need stones, and stones are literally everywhere around you, but you can't just pick these up like a regular person. You have to pick up special gigg upgessions, and they differ in color slightly and is a bit								
		And when you're done doing that, and being pretty proud of yourseft, you're going to meet the locals, that is hunter NECS Boars and Bears. Don't wony - the Bears will either hug you in a surprising way and make grunting sounds while you enjoy								
		MPCs? This game has MPCs?								
		Yes, and they're armod, but don't warry here either - the NECO are contemplating life in the game just like you are, they will go from spot to spot, oh, it's a dear, oh dear It's another deer, on there's a rabbit, there's another wabbit, on there you a								
		And it goes on.								
		The animals are constantly on the run, just like you. And so are the GHOST animals! YES Ghost animals, because before you know it, you'll hear something ROAR post you and you clicht see a thing. You check your speakers and your surroun								
		Speaking of sounds								
		Sounds are prentiful and random. If you see a beer or a boar - you will hear it roar instantly - or not, because even though the coder has put some effort in sound distance, you'll be anized of on how far or close the animals really are to you believe								
		Building stuff								
		Depends on how much you cellect, and you will run for hours just to get the satisfaction of owning a few sticks, and collecting sticks is just a matter of finding a half pint sized bush where you need to aim to the left and at an EXACT pick-up-sp								
		You will be equally susprised how much wood you need to collect, and there's plenty of trees, right? Wellyes, but not trees you can just chop down, as a lazy city coder, with world class mansthon running powers, your arms are as visas as not								
		When you strong forcing up, and moving output, a torong to make a your a torong to make a your professional p								

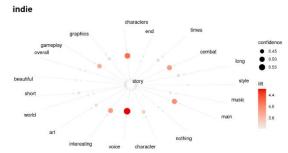
After:

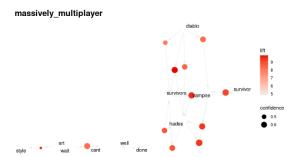
worst	got	multiplayer	worse	тар	buggy	weird	this	all	thence	smaller	paid	landscape	adding	arryway	steam
eat	believe	little	contenteven	adult	key	done	childygung	free	slow	paid	potential	lol	there	letting	developed
items	many	craft	bugs	sometimes	cant	never	ask	refund	point						
end	boars	king	realize	tshirt	job	color	hours	himself	spundssgunds	wood	differ	human	civilization	thar	burger
fixes	devs	keep	multiplayer	ripped	decided	happy	core	junk	saying	trial	broken	release	u	money	bs
mind	progress	dont	keep	devs	gameplay	buggy	least	hours	purely	nového	chest	human	comes	majority	scale
suspect	seen	promised	devs	worked	abandoned	voutube	endless	channel	next	later	significant	made	stand	delivered	continue
lots	sadly	pay	incomplete	alone	alpha	8000	users	world	no	released	etc	lighting	closed	here	recommendation
recommended		pc	pretty	player	theres	hits	cant	visuals	attacks	problemyou	effects				
	wonderful	retro	console	baking	used	lave	alternative	major	characters	BOOODGEER					
10	approprietly	theme	punches	not	movies	try	come	work	coinion	boxing	haif	Illegal	head	characters	
mortal	relies	said	realistic	simple	close	no	music	lower	etc	boxing	answer	stamina	health	opinion	dollars
arcade	previous	grain	multiplayer	mix	receptive	ready	gives	purely	license	valid	cut	story	positive	characters	besed
	morrison	keep	care	etci	little	tan	gyetyones	actually	this	simple	cup	story	wish	racky	added
	viking	king	mugged	decent	overrides	Job	fighter	Joy	dodged	story	tracks	variety	enemy	lightning	thunder
	fighter	training	anything	unlockedno	custom	real	fights	lacking	evander	looks	boxing	done	campaign	hoping	plays
	towards	found	next	tracks	involves	available	rocky	provided	sensational	big	boxing	that	brown	switchthe	learn
	decent	gameplay	lats	soundtrack	tighting	scores	graphics	hour	difficulty	there	teatures	choose	original	professional	
	fixed		this	forced	song	listen	fighting	easity	pick	shame	piease	want	option	match	developeraniesas
	flash	master	drago	mix	prime	easy	fighter	surprised	brawler	plenty	Wish	timing	fantastic	lang	made
	already	multiplaver				iob			least					rd	
	tighter	s	devs room	punches	fight versus	licensing	putting	eats	book	hours increases	fighter point	knock b	saying	streak	power buds
			sones	ado		liked	players iob	too	lines	hours			attog	native	fan
	eye rather	payloggreat			fly			retirement			everything	look	fighter		
		comments	become	triggered	world	seems	wish		characters	9000	players		portraits	conserved	receiving
	playability	reviews	glad	made	relaxing	id	mostly	negative	right	high	decision	bought			-
	dialogue	mostly	stunt	lose	immediate	characters	planned	irrelevant	correct	publicity	pespondedaugry	teministadouble	especially	antifeminists	
	concept	target	brain	entirety	simp	single	done	removal	cell	terrible	execution	ploy	developer	feminists	market
	sense	retirement	relate	made	wife	money	players	chinese	ponchinese	example	piots	only	random	happened	hard
	completed	day	characters	look	developers	unfair	within	indie	speaking	say	appearance	quite	reviews	female	understand
	southern	mengmeng	fishing	spent	simulates	used	line	view	story	aijus	retirement	currently	items	characters	granddaughter
discrimination		indian	production	lacks	full		society	lght	almost	groups	various	black	degree		
	got	Jack	devs	enviorments	addicting	usuable	dicint	little	screen	major	complete	smooth	supporting	bugs	thunder
	devs	worked	atmosphere	daily	hey	away	peaceful	gets	900	captured	takes	book	perfectly	easily	absolutely
atmospheric	updates	future	eat	task	rather	team	poorty	along	concept	camp	need	become	significantly	away	help
	working	st	fixed	multiplayer	outdoor	hunting	funlabs	gamets	correctly	realistic	genre	hazards	used	titles	never
	nneded	hunt	hours	D)V50	blurey	retty	screen	dowen	chuck	spooke	fast	refund	wuld	stuff	Isent
lagging	failed	horriable	data	everytime	everything	lost	leave	massive	save						
ramdom	got	diferent	happen	story	progres	lost	stuff	scrothing	point	pasentce	love	event	save	mission	load
forward	branches	care	hunting	found	specific	august	sense	locations	released	anywhere	developers	another	rocks	temble	logs
abandoned	fall	bush	tems	summer	burrow	taking	seeing	upgrades	according	clothes	since	bring	hired	getaber	wear
review	updates	addressed	decent	thosegraphics	used	need	missionstil	saying	everywhere	year	issue	lacking	86V	missiongame	e aug
price	state	along	hunting	concept	hours	next	brain	arma	reality	waythe	paint	press	bugs	alpc	players
	letdown	wonderful	however	total	money	come	hunt	etc	fish	sounded	excitement	waited	thought		
	lob	gameplay	finished	players	tunny	beautiful	hlok	different	self	done	small	tar	new	brillant	hard
		crash	seems	stable	messing	mode	player	single	potential	person	issues	ioins	except	friend	0000
	buas	released	follow	hyped	sale	big	bunch	abysmal	buy	person!		ponio	and a part of the same of the	ieiiu	a cop
	local	dialogue	hunting	surrounded	impacting	alone	story	caby serial	stavino	alter	vountaved	beyond	wids	for	stress

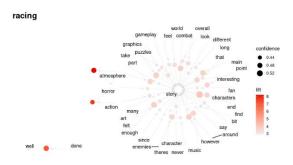
OUTPUT: Game analysis:

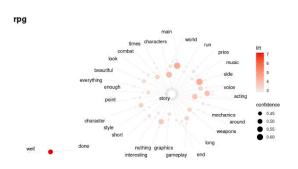


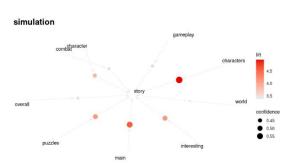


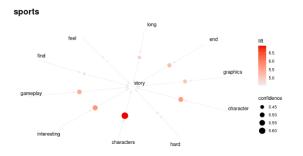


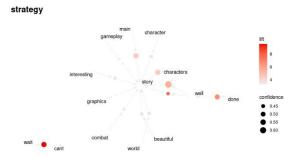




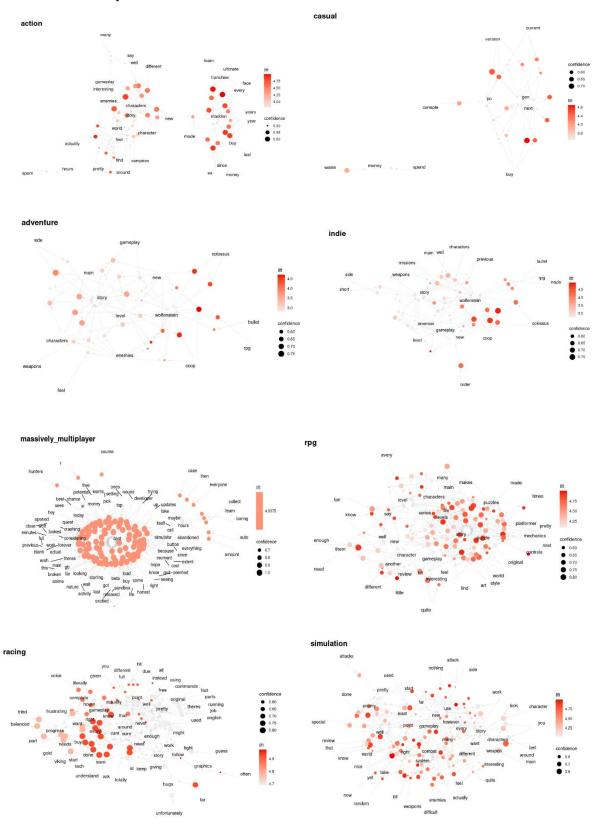


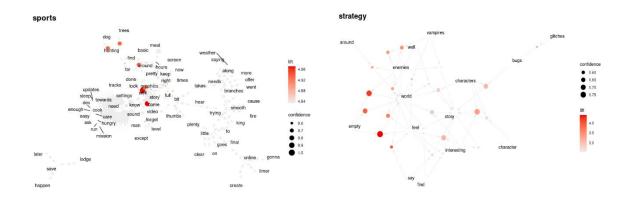






Game reviews analysis:





WHAT WE LEARNED: Negative reviews are much more scattered about. While RPGs center around story (which in this case might indicate a bad story) to a degree, the other plots are less centralized around a common theme which could indicate that some elements of a game could be good, but one bad element of a game can ruin the whole thing.

4. K-MEANS CLUSTERING This analysis uses the K-Means clustering algorithm to group Steam apps into distinct clusters based on the features total_reviews, total_positive_reviews, total_negative_reviews, and price. The goal is to identify patterns and similarities among apps.

DATA PREPROCESSING:

Converts publisher into numerical columns using One-Hot Encoding. Scales numerical features (Total_Reviews and Price) to have a mean of 0 and a standard deviation of 1.

WHY WE USED IT:

- 1. Clustering: With an optimal k=3, clusters group products into categories like high review/high price(premium), moderate review/mid-range price (popular mid-tier), and low review/low price (budget).
- 2. Visualizations: A scatterplot visualizes clusters by total reviews and price, with each cluster color-coded.
- 3. Key Insights: Products are segmented into distinct price and popularity tiers, aiding in market understanding.

MODEL EVALUATION (Accuracy Scores):

Inertia (Within-Cluster Sum of Squares):

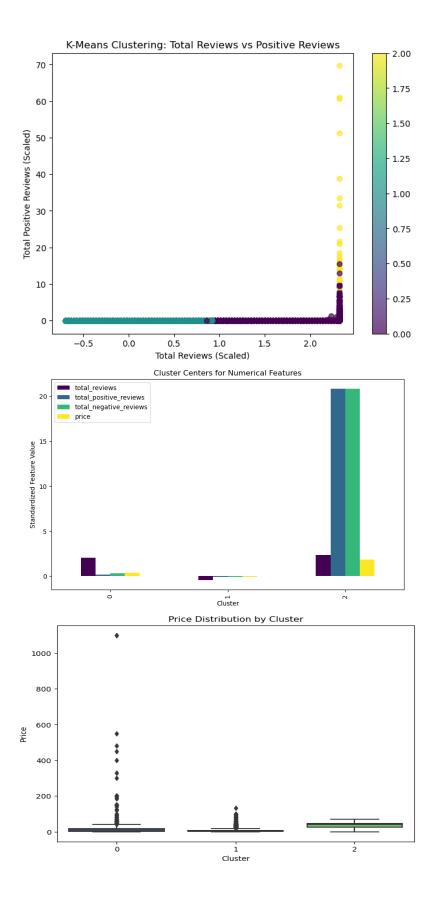
- Final inertia: 248.36, indicating a reasonable grouping of data points.
- Cluster Centers:
- Average prices for clusters:

Cluster 0: \$13.04 Cluster 1: \$5.94

Cluster 2: \$35.34

- Silhouette Score:
- An optional metric to evaluate clustering quality. Example: 0.52, indicating moderately well-separated clusters.

OUTPUT:



CONCLUSION

This project effectively studied patterns in the video game sector by gathering, refining, and presenting extensive data. The knowledge acquired can help developers, marketers, and stakeholders in making educated choices, matching product offerings with consumer preferences, and recognizing possible market opportunities. Future research might include a more in-depth examination of player involvement statistics and a wider investigation of upcoming gaming technologies.

In this project, we evaluated multiple models, including K-means, association rule mining, gradient boosting, CLIP model, to address various aspects of the game data analysis. Each model was assessed using metrics like accuracy, precision, recall, and F1-score to determine its effectiveness. The results demonstrated different outputs. While the models provided valuable insights, challenges such as data imbalance were addressed through techniques like hyperparameter tuning and data preprocessing. These findings highlight the importance of model selection and fine-tuning in deriving actionable insights from data.