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*School of Computing*

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Name: *Sakthignana Sundaram Somaskandan* Date: *6th December 2022*

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# Abstract

Product reviews have always been used to check the quality and legitimacy of a product, and product recommendations have played a vital role in creating big profitable corporate companies. The question I am answering is whether the sentiment expressed in game reviews impacts player engagement. Despite having limited time and data, I can prove my point and illustrate the findings in visualisation to communicate the results effectively to the audience. I concluded that review sentiment (measured by transforming the textual review to sentiment scores) and player engagement (measured by average player count) are related proportionally.

# Data Collection

I downloaded my dataset from [Kaggle](https://www.kaggle.com/" \t "_blank), called [Steam Reviews Dataset 2021](https://www.kaggle.com/datasets/najzeko/steam-reviews-2021" \t "_blank), which is in CSV format [1]. The dataset comprises 21 million user reviews (rows) of around 300+ games on Steam with a size of 8.17 GB. The reviews are from the Steam store [2]. Aside from the dataset obtained from Kaggle, I engineered and collected other datasets using specific features/columns from the Kaggle dataset, which will be discussed in detail under Data Exploration, Processing, Cleaning and/or Integration section.

The dataset contains the following attributes and data types.

|  |  |
| --- | --- |
| Attribute | Data type |
| Index | Number |
| Steam app ID | Number |
| App name | String |
| Review ID | Number |
| Language of review | String |
| Review text | String |
| Review creation timestamp | Number |
| Review latest update timestamp | Number |
| Whether review recommends the app | Boolean |
| Number of “helpful” votes for review | Number |
| Number of “funny” votes for review | Number |
| Score based on number of helpful votes | Number |
| Number of comments for review | Number |
| Whether review author purchased the app on steam | Boolean |
| Whether review author received the app for free | Boolean |
| Whether review was written during early access | Boolean |
| Review author steam ID | Number |
| Number of games review author owns | Number |
| Number of lifetime app reviews by author | Number |
| Author lifetime playtime of reviewed app | Number |
| Author playtime of reviewed app in last 2 weeks | Number |
| Author playtime of reviewed app at time of review | Number |
| Author time last played reviewed app | Number |

The three aspects of big data are present in my dataset in the following ways.

Firstly, it has variety: I used the app\_id column (Steam-specific game identifier) from the Kaggle dataset to fetch game statistics on each of the 300+ games for which data is available as extra data points to gain a deeper understanding of player engagement.

Additionally, the game statistics data is updated hourly and made available through the same API endpoints I’ve used. This fulfils the velocity aspect as the data is in motion and updated constantly.

Lastly, it has volume: the Kaggle dataset contains 21,612,444 reviews. The dataset I gathered contains 21,288 rows of game statistics of size 1.8 MB.

# Data Exploration, Processing, Cleaning and/or Integration

The story I wanted to convey to the viewer required data that is not readily available in the dataset. Therefore, I had to collect other datasets using certain information from the Kaggle dataset, namely game ID. The Game statistics and Sentiment analysis sections below outline the approach and the data points obtained.

## Game statistics

Steam published the API endpoint I used on RapidAPI, an online API marketplace. Developers use RapidAPI to discover and connect to thousands of APIs. I made calls to the following endpoint, with unique game/app IDs fetched from the Kaggle dataset [3]. The game statistics are available on [steamcharts](https://steamcharts.com/) [4].

|  |
| --- |
| https://steamcharts.p.rapidapi.com/api/v1/games/{id} |

I was able to collect the following information from executing the above call.

|  |  |
| --- | --- |
| Attribute | Description |
| ID | Steam app ID |
| Name | Game name |
| Month | Month and year associated with the statistics provided |
| Average players | Average number of players during a specific month |
| Gain | Number of players joined or left the game since the last month |
| Gain in percent | Number of players joined or left the game since the last in percent |
| Peak players | The greatest number of players in the game during a specific month |
| Playing 12-hours ago | Number of players in the game 12 hours ago |
| 24-hour peak | The greatest number of players in the game in the last 24 hours |
| All-time peak | The greatest number of players in the game over the game’s lifetime |

The collected dataset needed to be cleaned for visualisation, i.e., the ‘Month’ column had ‘Last 30 days’ as entries, whereas the rest of the data are in the format [Month] [Year]. Therefore, I used pandas (python data analysis library) to replace all instances of ‘Last 30 days’ with ‘October 2022’.

The Jupyter notebooks can be found in the GitHub repo as well as in the submission zip file. The associated Jupyter notebooks are data\_cleaning.ipynb and data\_gathering.ipynb.

## Sentiment analysis

I decided to use the review text provided by the Kaggle dataset to compute the sentiment score associated with the text. I made use of the TextBlob library to carry out the sentiment analysis. TextBlob is a python library for processing textual data and provides a consistent API for common Natural Language Processing (NLP) tasks [5]. The sentiment analysis API returns a named tuple of the form Sentiment (polarity, subjectivity). The polarity score is a float within the range [-1.0, 1.0] where -1.0 is entirely negative, and 1.0 is altogether positive. The subjectivity is a float within the range [0.0, 1.0], where 0.0 is very objective, and 1.0 is very subjective. I used the polarity score for visualisation as it shows the overall sentiment of a review.

Note: I performed sentiment analysis on English reviews only and filtered non-English reviews out of the dataset.

|  |
| --- |
| Sentiment Analysis Pseudocode |
| Read in the Kaggle dataset  Filter out unnecessary columns  Filter out reviews that are not in English using ‘language’ column value  Clean the review text by removing stop words and unnecessary characters  Perform sentiment analysis on the cleaned review text  Collect the polarity values  Append the polarity values to the Kaggle dataset dataframe  Export to csv file |

I collected a polarity score in the range [-1.0, 1.0] for each review in the Kaggle dataset. This dataset contains the following information.

|  |  |
| --- | --- |
| Attribute | Description |
| Steam app ID | Steam app ID |
| App name | Game name |
| Review ID | Identifier for the review text |
| Language of review | Language used in the review text |
| Review text cleaned | The cleaned review text – removed stop words, punctuations and other unnecessary characters |
| Polarity | The sentiment score in the range [-1.0, 1.0] indicating the review emotion, i.e., positive, negative, or neutral |
| Review creation timestamp | The date/time when the review was posted |

The Jupyter notebooks can be found in the GitHub repo as well as in the submission zip file. The associated Jupyter notebook is steam\_reviews\_sentiment\_analysis.ipynb.

## Data exploration

The charts below are not the final visualisations. I find it easier to get to know the data by visual cues; that is the reason why I included these graphs. I first explored the data by looking at the language ratio – the reviews written in English dominated the dataset, as seen in Figure 1. I also utilised a tree map to visualise the same language split, as seen in Figure 2.

Chart

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Figure : Language Ratio

Chart, treemap chart

Description automatically generated

Figure : Language Split as a Tree map

This gave me the confidence that analysing the English reviews alone for sentiment analysis can capture a game’s overall sentiment better than the other available languages.

Additionally, I explored the polarity split among the English reviews across all 300+ games in the dataset, as shown in Figure 3.

Chart, pie chart

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Figure : Polarity Split

Instead of strictly choosing attributes from one dataset, I gathered the data I needed, using certain information from the big dataset to convey my story effectively.

# Visualisation

Chart, bar chart

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Figure : Average Players – Player Engagement

Graphical user interface, chart, line chart

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Figure : Review Sentiment

Chart, bubble chart

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Figure : Polarity Overview - English Reviews

## Choice of chart types

I am showing the relationship between review sentiment and player engagement over time. Player engagement decreases as the review sentiment goes in the negative direction. As I am correlating average players in Figure 4 with average polarity in Figure 5 over time, a bar chart and a line chart effectively communicate the increase and decrease in the quantities. Bar and line charts are good at presenting categorical data that the common people easily understand, so there is no need to educate the audience on how to read the visualisation. Lastly, the bubble chart in Figure 6 lets the audience quickly understand the overall proportion of different sentiment polarities for a specific game.

The data types of the visualised attributes are as follows. The polarity overview is a transformed view of the Sentiment Analysis line chart.

|  |  |
| --- | --- |
| Attribute | Data type |
| Average players | Number |
| Polarity sentiment score | Floating point number |
| Polarity overview | Categorical |

The polarity overview chart has the following tableau filter. The Sentiment Analysis line chart has visualised the average Polarity Converted value.

|  |
| --- |
| IF [Polarity Converted] < 0 THEN "Negative"  ELSEIF [Polarity Converted] > 0 THEN "Positive"  ELSE "Neutral" END |

## Design choices

I designed an interactive dashboard on Tableau with all three charts in one view with a filter that lets the audience pick and choose a game, as shown in Figure 7.

Chart, histogram

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Figure : Player Sentiment Dashboard

The reasons for my design decisions:

* I structured the dashboard this way as it would be natural to compare and contrast the two charts in the centre and use the smaller right-hand side bubble chart as supplementary information.
* My choice of colour for the Polarity Overview chart is red, green and yellow as most people readily associate green with positive, red with negative and yellow with neutral (traffic light analogy). As the Polarity Overview chart is easily interpretable, the audience can focus on the main two charts in the dashboard’s centre.
* My choice of colour for the Sentiment Analysis chart is also deliberately made deep orange as it falls in the negative direction and navy as it rises in the positive direction. Deep orange is close to red, indicating an undesired outcome, and navy is a pleasant and neutral colour showing the desired result.
* I have used a line chart to display the polarity fluctuations to reduce the cognitive load on the audience when comparing the two graphs, as it would be arduous to compare two similar chart types.

## Interactivity

I have the data for 300+ Steam games. Hence, I have provided a filter on the top right-hand side of the dashboard to allow the audience to interact and analyse the corresponding results for a specific game.

This aids in telling my story as we can compare the results across many different game titles. I understand the story that I want to convey is only valid when the hypothesis applies to many samples (games). Therefore, avoiding any misleading information propagating to the audience.

Interactivity is demonstrated in the video screencast.

## Tools and libraries

The tool that I used to create the visualisations is Tableau [6]. Python was used to gather data from Steam using one of their API endpoints and to clean the acquired data to aid in the visualisations. The python libraries that I used are:

* Matplotlib
* TextBlob
* Pandas
* Requests
* Json
* Time

# Conclusion

The outcome of my visualisation successfully illustrates the relationship between review sentiment and player engagement. The relationship is proportional for most games, i.e., as the review sentiment increases (goes in the positive direction), the player engagement/game popularity increases. It is important to note that the sentiment scores were computed only for English reviews, and I filtered out other language reviews. As a result, the relationship proportionality may only convey accurately for some games, such as those with a high percentage of English reviews. However, the proportional relationship will be more visible when all language reviews are processed and given a sentiment score.

The biggest problem with the data was that the reviews were in textual format and the other columns in the dataset were very straightforward for a good and insightful visualisation project. I spent most of my time thinking of ways to expand upon the obtained dataset from Kaggle – which I did by gathering player statistics and performing sentiment analysis on the review text so that the visualisation is accurate and valuable to the audience.

In terms of improvements, I wanted to show one chart with three axes – timeline on the x-axis, average players on the left-hand side y-axis and average polarity on the right-hand side y-axis. The two y-axis scales would be different as average players is in the range [0, 200000] and average polarity is in the range [-1.0, 1.0]. I tried to get it on Tableau but got an error: Error Code: 73F9639A (the full stack trace can be found on my GitHub repo). A single chart would greatly benefit the audience by reducing the cognitive load and effectively communicating my story in a much smaller time frame.

# Datasets

The datasets used to create the visualisations are available to download [here](https://drive.google.com/drive/folders/1sP3HK-gHqvZ6jx_dlEvE-caYRJRl_bPQ?usp=share_link). The submission zip file includes the Tableau file and the other relevant Jupyter notebooks. The video file of the screencast can be accessed via the same Google Drive link provided above.

# Github Repo Link

<https://github.com/sur-sakthy/data-visualisation-project>

# References

[1] M. M, “Steam Reviews Dataset 2021 | Kaggle,” 2020. https://www.kaggle.com/datasets/najzeko/steam-reviews-2021 (accessed Nov. 26, 2022).

[2] “Welcome to Steam,” *Valve Corporation*, 2022. https://store.steampowered.com/ (accessed Dec. 05, 2022).

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