Data Science Project Presentation

PREDICTING THE SUCCESS OF A VIDEO GAME.



Students:

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About Our Project

The video game industry continues to expand year after year. Every studio/developer wants to grow revenue and reach out to more players and gaming communities.

The developers depend primarily on websites that aggregate reviews of video games (in terms of success).

The developers may see what gamers think about the next game by examining and evaluating this data and acting accordingly.





Research questions:

Can we forecast the success or failure of a released video game based on user and professional factors?

EDA:

What factors influence a video game's success?

Can we find unexpected results? (not logical)



The Process

02

03

04

Data acquisition

Data cleaning

EDA

Machine Learning

Step 1 - Data acquisition (API and crawling)

Step 2 – Data Handling

Step 3 – EDA (visualization and statistical tests)

Step 4 – Machine learning

Step 5 - Conclusion



Data Sources

https://www.metacritic.com

Crawling 01

https://steamspy.com

API 02

Metacritic - Selenium, BeautifulSoup, Pandas Raw data size: 32K

SteamSpy – API, Pandas, Json, requests Raw data size : 85K

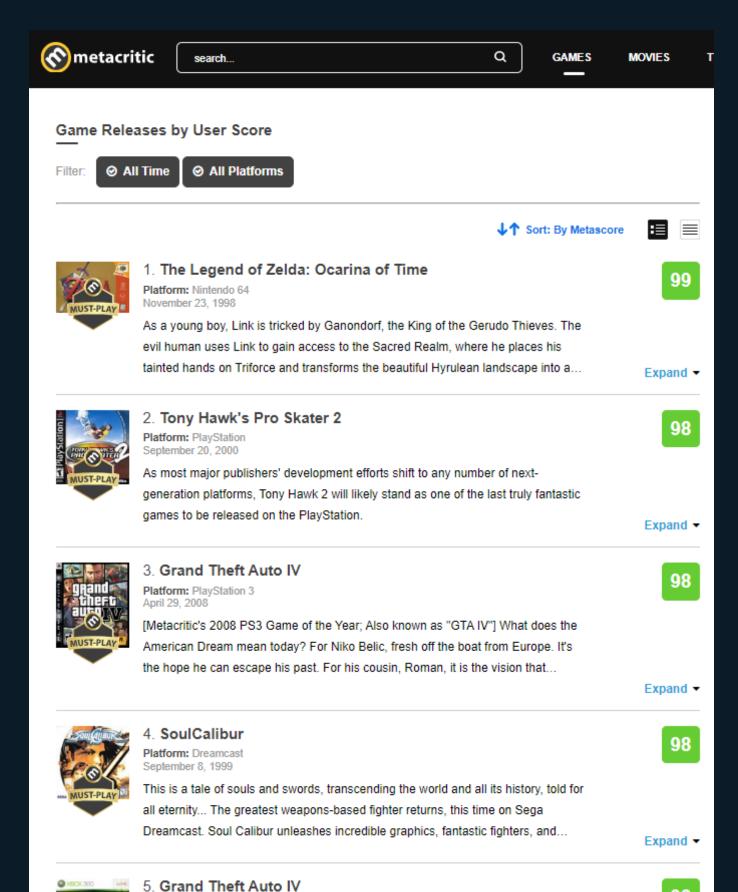
Metacritic

We compiled a list of all game URLs on the website from 2005 through the end of 2021.

Created a Selenium driver that iterated over the URLs and crawled across the sites. Downloaded the page source for each page.

Created a beautiful soup object that holds the page source and scraped the data of all games on the page, saving it in a dictionary that is needed to build a data frame.

We added a new column to the main data frame called "score" and iterating through both the final and Metacritic data frames to match the game's name and apply the appropriate score to that game.



MetaCritic

```
#Setting up selenium
#install service for selenium access
s=Service(ChromeDriverManager().install())
#toggle needed options
options = Options()
options.headless = True #open browser unseen
#create driver
driver = webdriver.Chrome(service=s, options=options)
for mc years, mc details in zip(meta critic list years, meta critic detail list):
    driver.get(mc_years)
    ps = driver.page source
    soup = BeautifulSoup(ps, 'html.parser')
    page_numbers = int(soup.find("li", class_ = "page last_page").find("a").string)
    for i in range (0, page_numbers):
        driver.get(mc_years + '&page=' + "{0}".format(i))
        ps = driver.page_source
        soup = BeautifulSoup(ps, 'html.parser')
        meta critic detail list[mc details].append(soup.find all(class = "clamp-summary-wrap"))
driver.quit()
```

SteamSpy

Getting the data from SteamSpy was made by a API call from the website. Some columns, however, were unrelated to our study.

We used the API to gather almost 10 000 rows and saved them as a data frame.



Return format for an app:

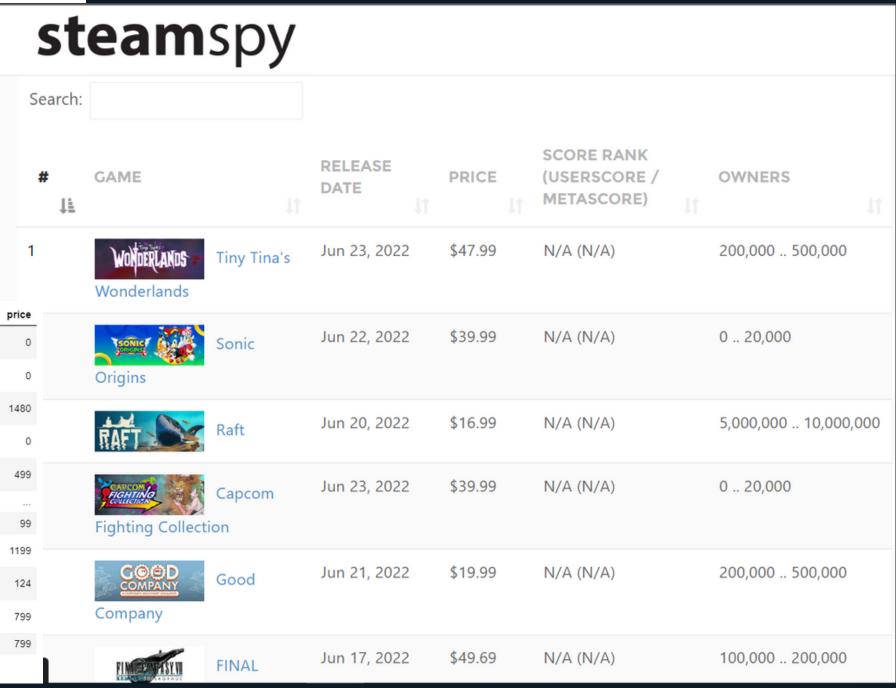
• appid - Steam Application ID. If it's 999999, then data for this application is hidden on developer's request, sorry.

Q.

- name game's name
- developer comma separated list of the developers of the game
- publisher comma separated list of the publishers of the game
- · score rank score rank of the game based on user reviews
- owners owners of this application on Steam as a range.
- average_forever average playtime since March 2009. In minutes.
- average_2weeks average playtime in the last two weeks. In minutes.
- median forever median playtime since March 2009. In minutes.
- median_2weeks median playtime in the last two weeks. In minutes.
- · ccu peak CCU yesterday.
- · price current US price in cents.
- · initialprice original US price in cents.
- · discount current discount in percents.
- tags game's tags with votes in JSON array.
- · languages list of supported languages.
- · genre list of genres.

	name	developer	publisher	positive	negative	owners	average_forever	median_forever	price
0	Counter-Strike: Global Offensive	Valve, Hidden Path Entertainment	Valve	5718191	761211	50,000,000 100,000,000	788/16	6493	0
1	Dota 2	Valve	Valve	1467658	297030	100,000,000 200,000,000		964	0
2	Grand Theft Auto V	Rockstar North	Rockstar Games	1153983	208800	20,000,000 50,000,000		6441	1480
3	PUBG: BATTLEGROUNDS	KRAFTON, Inc.	KRAFTON, Inc.	1146769	892200	50,000,000 100,000,000	71155	6620	0
4	Terraria	Re-Logic	Re-Logic	951689	20646	20,000,000 50,000,000	6176	1739	499
9634	HEDE Game Engine	Hede Games	Hede Games	0	7	50,000 100,000	0	0	99
9635	League Space	EURO GAMES STUDIO	EURO GAMES STUDIO (ESP)	0	1	50,000 100,000	0	0	1199
9636	RagDoll MadDoll	Team Booky	Dystopian Edge Publishing	0	1	50,000 100,000	0	0	124
9637	Operation: VICUS	Ilja Soutchilin, Tom Berger	Ilja Soutchilin, Tom Berger		2	50,000 100,000	0	0	799
9638	RACE On	SimBin	SimBin	0	0	100,000 200,000	0	0	799
9639 rows × 9 columns									

SteamSpy



Data handling

In the 'publisher' and 'developer' columns, there were some NaN values. We duplicated the 'developer' name into the 'publisher' and vice versa instead of dropping those rows.

We saved alot of rows and data by doing so. We also removed duplicates and limited edition games.

The values of the 'price' were changed from cents to dollars.

The values for 'owners' were a range of owners, we replaced them with the average of that range and renamed the column 'owners approx.'

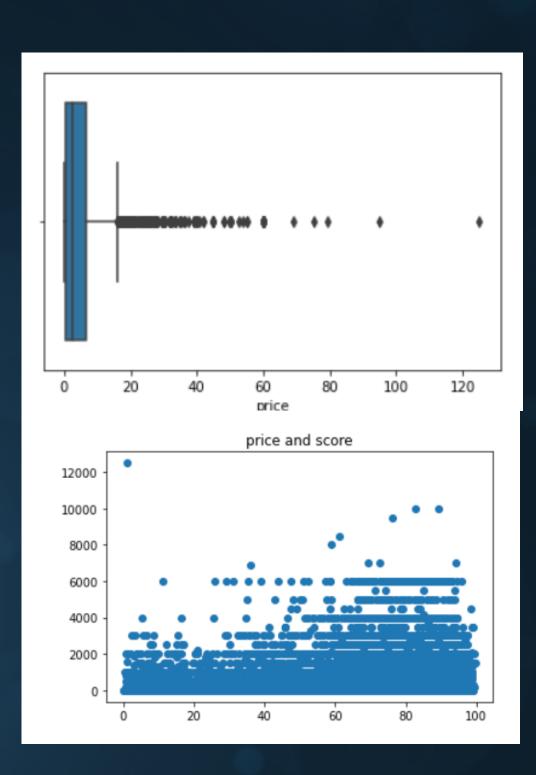
Some titles were not listed on Metacritic. We used the 'positive' and 'negative' values, which describe the quantity of positive and negative input, to handle their'score' value from SteamSpy.

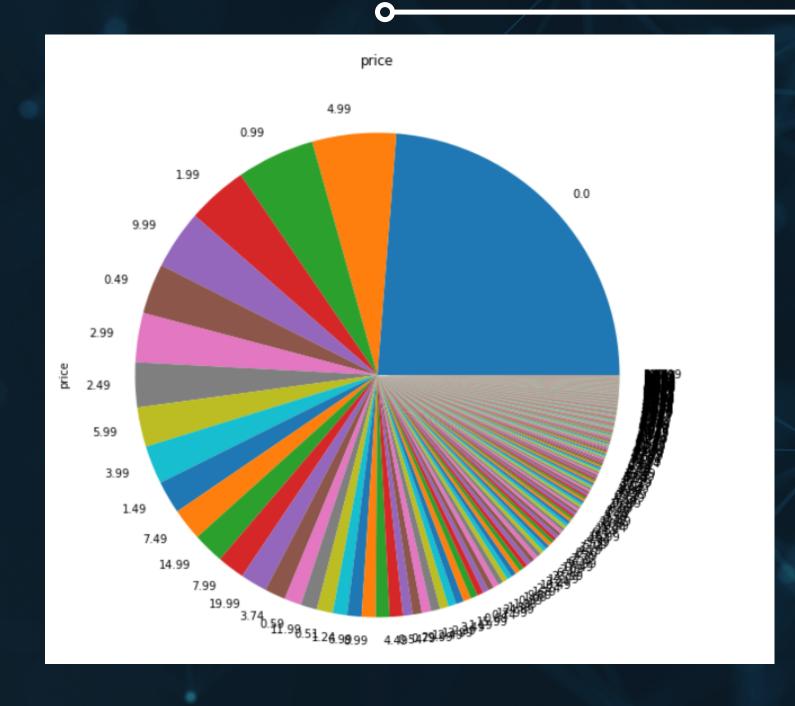
EDA and statistical tests

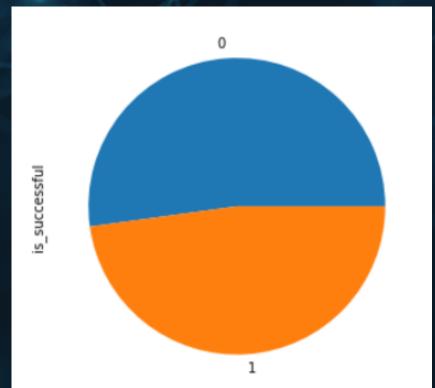
The first step was to use a bar plot to represent the numeric columns. To better understand the distribution, we scaled each column.

The second step was to examine the relationships between the 'score' column and the other numeric columns. We utilized the Spearman approach because none of the columns had a normal distribution. The scatter plot between score and other columns, as well as the actual correlation value between said columns, were also shown.

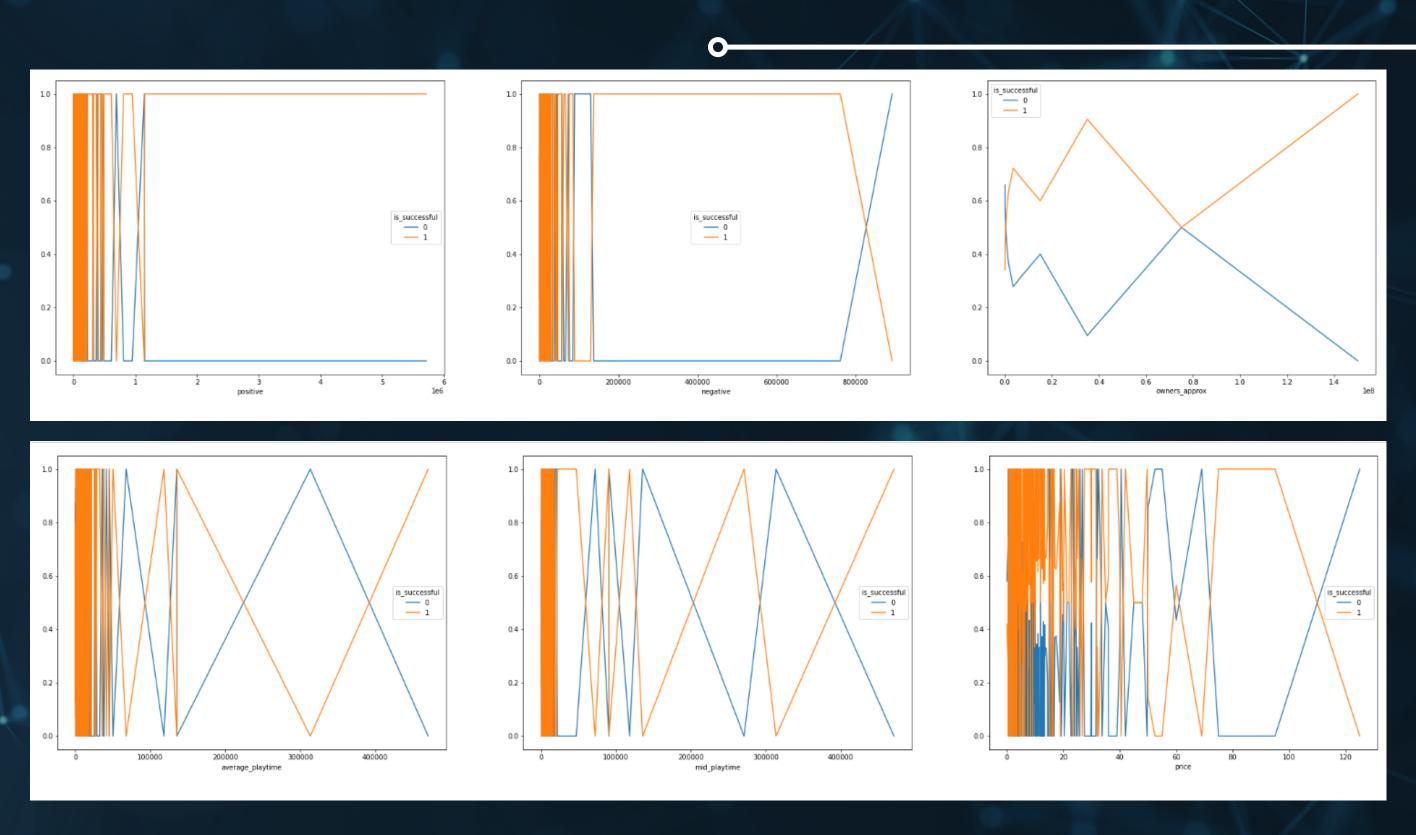
Eda



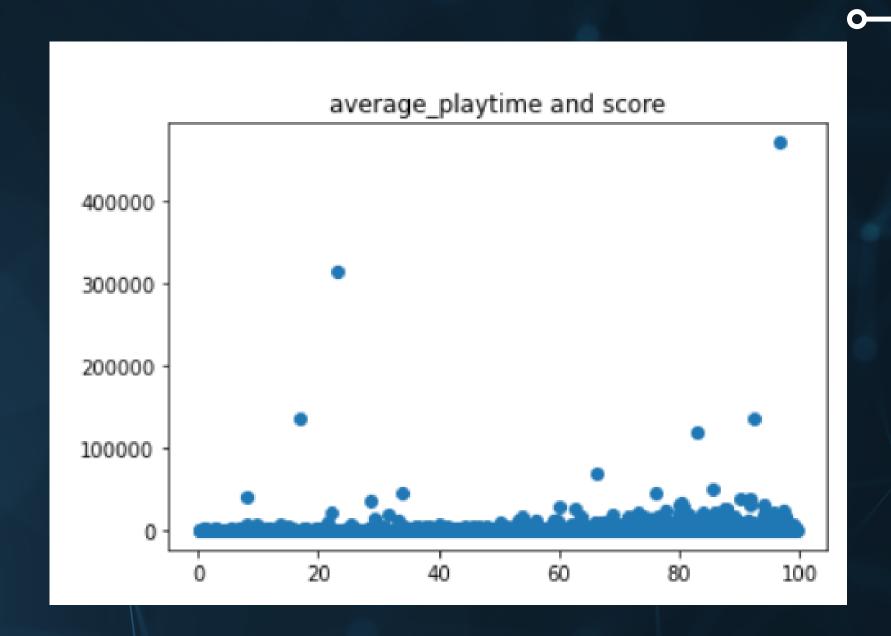


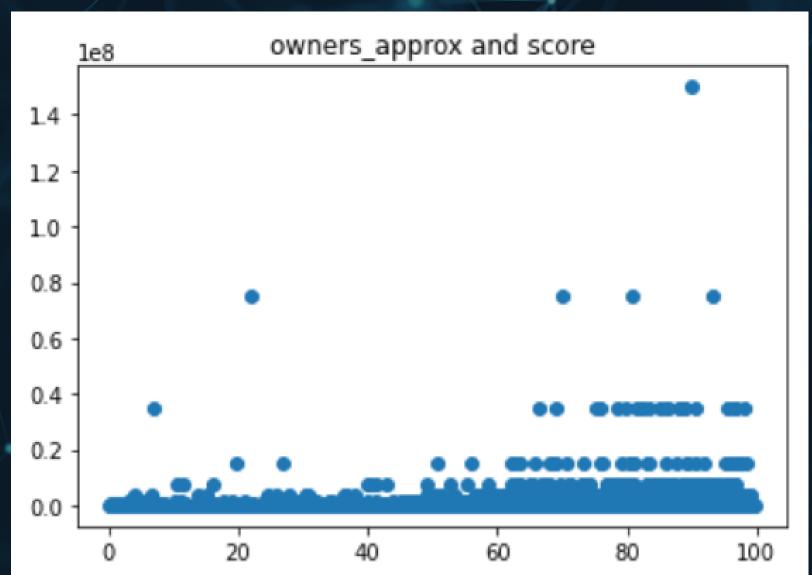


Eda



Eda





Machine learning

We employed a supervised method in the machine learning phase. All of the numeric columns were included in the feature vector (X), except for the 'is successful' and score columns ('is successful' is the goal column (y)). We utilized logistic regression to train the model, which is designed for binary problems (in our instance, 0 or 1).

The accuracy of the prediction was impressive: 85%. We divided the data frame into training and testing groups and compared the measurements of Logistic regression and the random forest model as well.

Our major strategy was to use logistic regression, which yielded an accuracy of 85%. As well as that we did the ensemble wombo combo just for the fun of it.

Conclusion

1. The unscaled model produced excellent results.

Eda:

- 2. We discovered that some characteristics can indeed indicate whether a game will succeed.
- The price and the postive reviews of a game really matter to sigma gamers.
- 3. A game can be successful even tho the amount of negative reviews is high and the game can be unsuccessful and have a very high price.

Thank You!

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