Predicting Video Game Review Scores

Team Amazing
DATS 6103, Final Project
Hyunjae Cho, Chenyang Lu, Michael Pagan

Introduction

As the next generation of gaming is among us, hundreds, if not thousands, of new (or remastered) games will be released in the coming years to keep gamers entertained. One way to know if a game is worth purchasing is to consider the reviews a game gets. Games do not usually flop in the reviews and our data show that, in fact, most games do quite well, with an average score of about 7/10. However, not all reviews are equal - recent controversy over skewed scoring have come to light and some groups like Kotaku have even stopped giving out numeric ratings in their reviews. Thereby, it is clear that it is in a gamer's best interest to seek multiple outlets for reviews since the outcome can vary depending on the group that reviewed it.

Our group is interested in using the reviews from popular websites for video game reviews to predict the ratings of the next generation's games. Our project focused on scraping popular websites for video game reviews to create a model that can predict a game's review score.

SMART Question

Given the importance a video game's review may play in a gamer's decision to buy a game, and the potential for disparate reviews to come from the various media outlets for reviews, we asked the following:

Can we predict the review score a game will get based on the ratings from three major review websites for various genres and platforms?

However, we were forced to refine this question after building our linear regression as there were insufficient features in the model to accurately predict score. Thus, we asked:

Can we predict if a game will get a review score of 80% or better *based on the ratings from three major review websites for various genres and platforms?*

To answer these questions, we used several modeling techniques to predict the review scores.

Methods

The Selenium and BeautifulSoup Python libraries were used to scrape the title of the game reviewed, the platform it was reviewed on, the genre of the game, and the score it received from Metacritic, OpenCritic, and GameSpot with a total of 46,958 data points captured between all three sites. To be consistent between sites, only modern platforms were considered, such as PlayStation 4 and Xbox One, though the sites had reviews for nearly every platform ever created. Similarly, we narrowed the scope of the genres each site reviewed. Since Metacritic had a finite list of 17 genres compared to the tens of genres available on the other sites, Metacritic's genres were used as the metric to obtain reviews from the other sites. However, there is some margin of error in this approach as there may be discrepancies in how a site classifies a game, such as "Sports" vs. "Soccer". Nevertheless, the following platforms and genres were used:

Platforms:

- PC
- PlayStation 3
- PlayStation 4
- PlayStation Vita
- Nintendo 3DS
- Nintendo Switch
- Nintendo Wii
- Nintendo Wii U
- Xbox 360
- Xbox One

Genres:

- Action
- Adventure
- Fighting
- First-person
- Flight
- Party
- Platformer
- Puzzle
- Racing
- Real-Time

- Role-Playing
- Simulation
- Sports
- Strategy
- Third-Person
- Turn-Based
- Wrestling

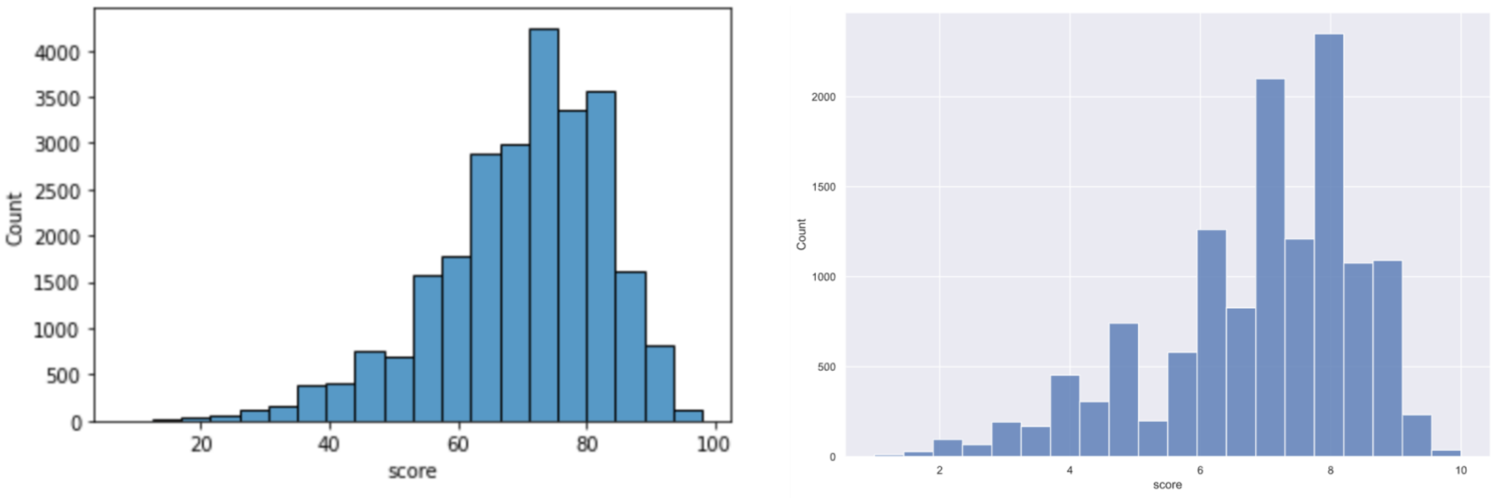
Linear regression models were constructed using a game’s score as the target variable and the platform and genre as the independent variables. Both independent variables were coded numerically to successfully integrate them into the model.

Logistic Regression, KNN (neighbors = 7), Linear SVC, SVC (gamma = auto), and Decision Tree (criterion='entropy', max_depth=10, random_state=1) classification models were made to predict if a game would score 80% or better.

All models were created using the scikit-learn Python library.

Exploratory Data Analysis

Data was scraped from OpenCritic, Metacritic, GameSpot using Selenium and BeautifulSoup and 46,958 data points were obtained. The score distribution for each site was relatively similar for GameSpot and Metacritic; OpenCritic rated games more highly than the other two sites **(Figure 1, Table 1**).



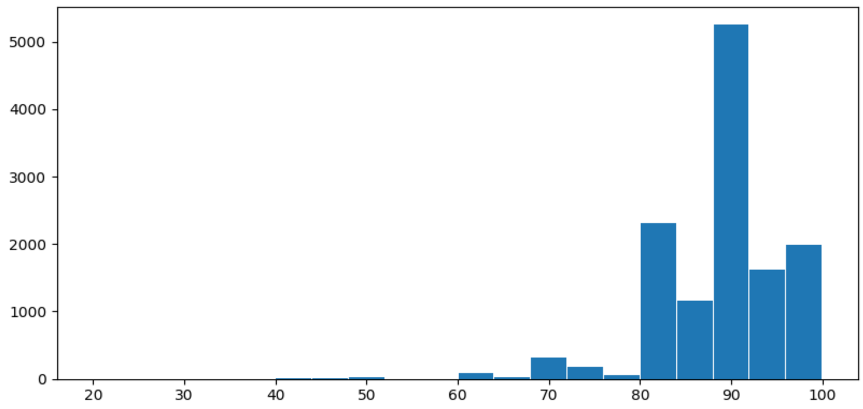


Figure 1: Score distribution from each website. Clockwise from top-right: Metacritic, GameSpot, OpenCritic.

Table 1: Mean and median for the score distribution of each website.

Site	**Mean**	**Median**
OpenCritic	87.67	88
Metacritic	69.68	72
GameSpot	6.88	7

Between all three sites, games were most numerous on PC (**Figure 2, Table 2**); action was the most frequent genre (**Figure 3, Table 3**).

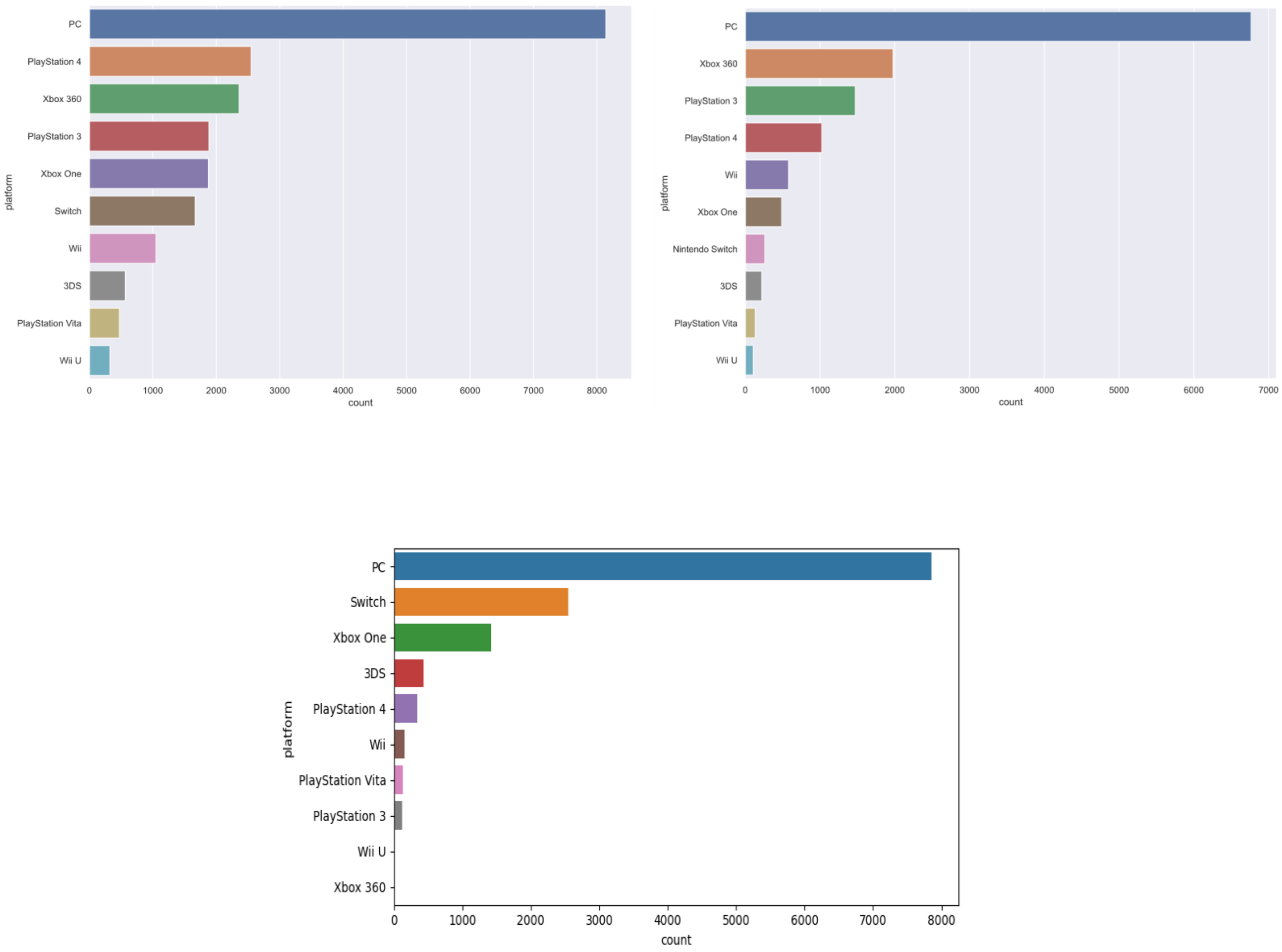
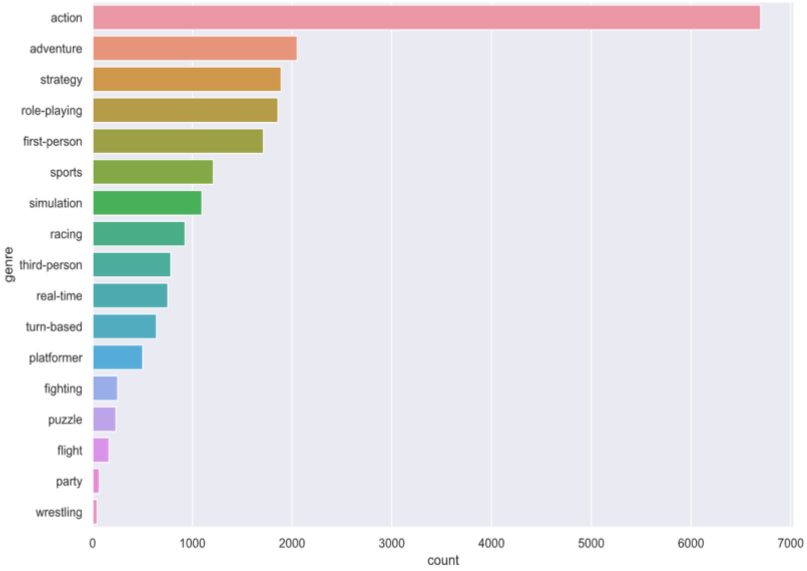


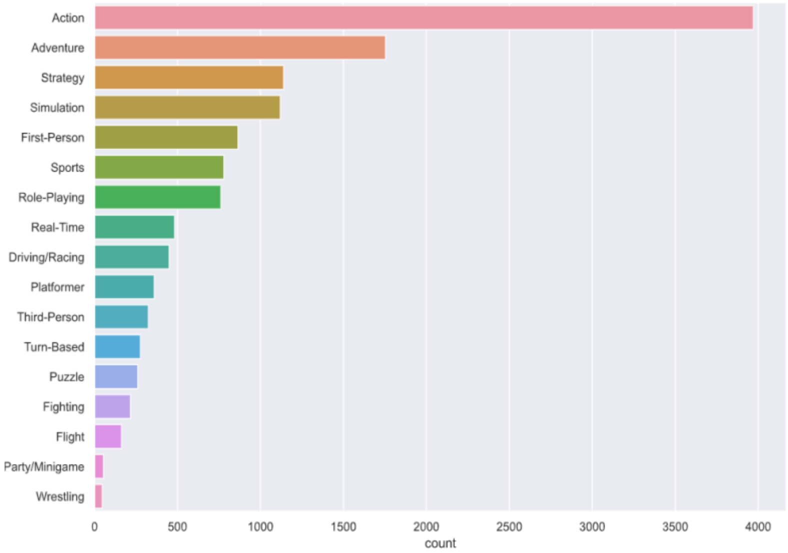
Figure 2: Count of platforms scraped from each website. Clockwise from top-right: Metacritic, GameSpot, OpenCritic.

Table 2: Platform counts from each website.

Platform	OpenCritic	Metacritic	GameSpot
PC	7856	8140	6766
Xbox 360	8	2360	1977

PlayStation 3	126	1884	1472
PlayStation 4	337	2549	1024
Will	153	1050	578
Xbox One	1416	1876	488
Nintendo Switch	2553	1668	263
3DS	436	566	221
PlayStation Vita	134	474	133
Wii U	8	323	107
Total	**13027**	**20890**	**13029**





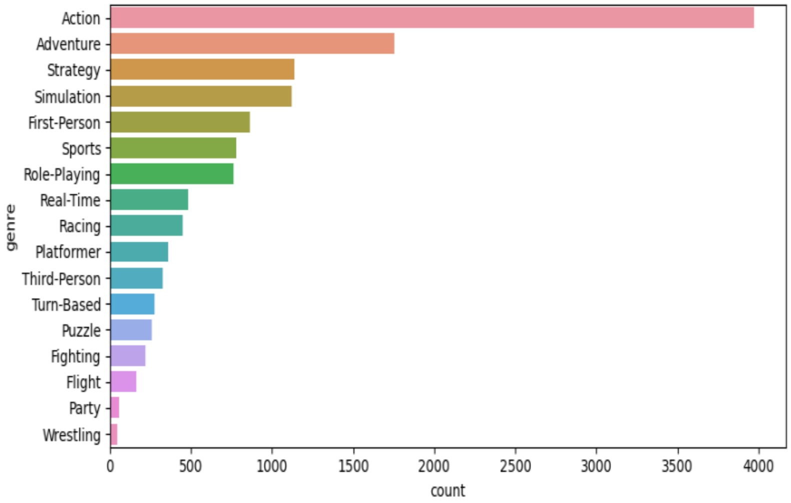


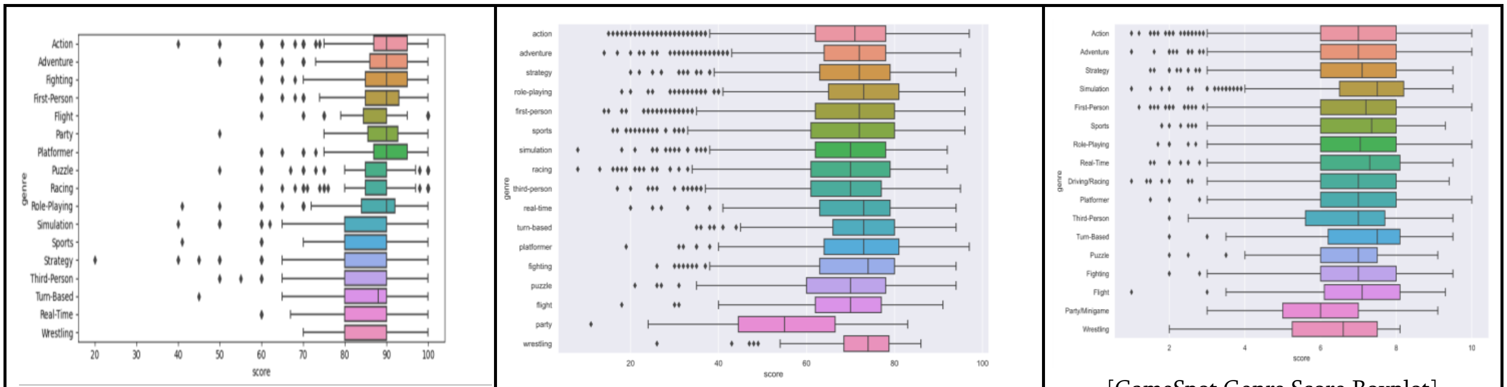
Figure 3: Score count by genre. Clockwise from top-right: Metacritic, GameSpot, OpenCritic.

Table 3: Number of Counts by Genres

Genre	OpenCritic	Metacritic	GameSpot
Action	7590	6698	3971
Adventure	1658	2052	1754
Fighting	90	251	217
First-Person	335	1713	865
Flight	3	165	217
Party	41	67	54
Platformer	213	502	360
Puzzle	47	234	261
Racing	21	927	450
Real-Time	90	754	483
Role-Playing	91	1859	762
Simulation	460	1096	1120
Sports	458	1211	780

Strategy	1560	1891	1140
Third-Person	156	784	325
Turn-Based	21	640	277
Wrestling	51	146	47
Total	**12885**	**20990**	**13083**

As illustrated in **Figure 4**, OpenCritic reviewers tended to give higher scores than Metacritic and GameSpot. The first and third quartile of the OpenCritic scores ranged from 80 to 95. On the other hand, Metacritic and GameSpot boxplots range from 60 - 80 and 6 - 8, respectively. The party genre scored markedly lower than others, receiving a score ranging from 40 to 65 and 4.5 - 6.5 for Metacritic and GameSpot, respectively.



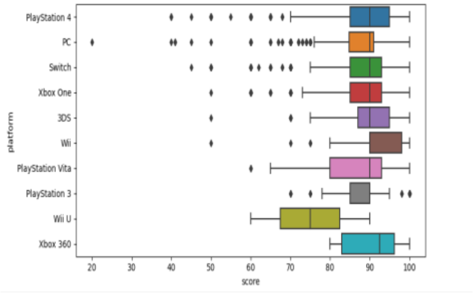
[OpenCritic Genre Score Boxplot]

[Metacritic Genre Score Boxplot]

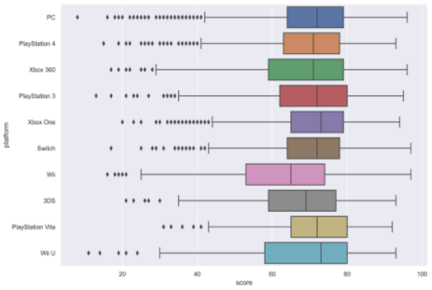
[GameSpot Genre Score Boxplot]

Figure 4: Game score by genre

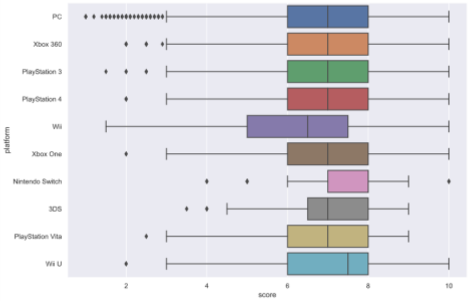
We had similar results that reviewers from OpenCritic tended to give scores between 80 - 9. Scores ranged from 60 - 80 and 6 - 8 in Metacritic and GameSpot, respectively. Interestingly, Wii U had lower scores than other platforms in OpenCritic, and Wii had lower scores in Metacritic and GameSpot (**Figure 5**).



[OpenCritic Platform Score Boxplot]



[Metacritic Platform Score Boxplot]



[GameSpot Platform Score Boxplot]

Figure 5: Game score by platform

Modeling

Linear Regression

We first built a linear model with two explanatory variables - platform, genre - but the model was a poor fit. Test and train scores for the linear regression (**Figure 6**) were all very small - no one model breaking >0.01 accuracy (**Table 4**).

$$h(x_i) = \beta_i + \text{Platform}(x_i) + \text{Genre}(x_i)$$

$$\text{OpenCritic: } Score_i = 88.0431 + 0.0820 * platform_i - 0.0054 * Genre_i$$
$$\text{Metacritic: } Score_i = 67.2912 + 0.2020 * platform_i - 0.2630 * Genre_i$$
$$\text{GameSpot: } Score_i = 6.8020 + 0.0022 * platform_i + 0.0157 * Genre_i$$

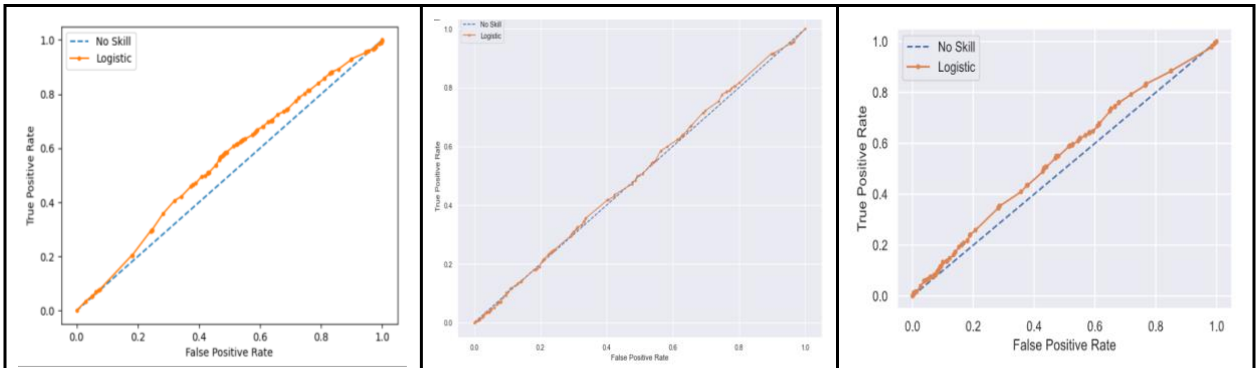
Figure 6: Linear regressions score as a function of platform and genre for each website

	Train Score	Test Score
OpenCritic	0.00290	0.00160
Metacritic	0.00035	0.00075
GameSpot	0.00280	0.00380

Table 4: Linear regression test and train score

Classification models were then constructed to understand if we could predict if a score would receive an 80% or better rating from each of the three sites. We first utilized a logistic regression to fit our data to predict the scores. The resulting test and train accuracies for the logistic regression were high. However, **Figure 7** shows that the ROC-AUC value was low and our logistic regression was also poor fit.

Logistic Regression



[OpenCritic ROC-AUC]
Logistic ROC AUC value : 0.550

[Metacritic ROC-AUC]
Logistic ROC AUC value : 0.508

[GameSpot ROC-AUC]
Logistic ROC AUC value : 0.547

Figure 7: Logistic ROC AUC curve

Several other classification models were explored, including K-nearest neighbor, Decision Tree, SVM, and Linear SVM models (**Table 5**). Evidently, the models often predicted no better than the null model (**Appendix**), but the KNN models for each site appeared to be among the best models relative to the other classifications models that were made (**Figure 8, Table 6, Table 7**).

OpenCritic					
	Logistic	KNN	Decision Tree	SVC	Linear SVC
Score (train)	0.6165	0.7532	0.6581	0.6567	0.6257
Score (test)	0.6020	0.7479	0.6546	0.6152	0.6152
Cross Eval	0.5368	0.5652	0.3599	0.6299	0.6299

Metacritic					
	Logistic	KNN	Decision Tree	SVC	Linear SVC
Score (train)	0.7745	0.7678	0.7748	0.7744	0.7744
Score (test)	0.7726	0.7673	0.7726	0.7725	0.7725
Cross Eval	0.6784	0.6192	0.7499	0.7740	0.6384
GameSpot					
	Logistic	KNN	Decision Tree	SVC	Linear SVC
Score (train)	0.6493	0.6317	0.6569	0.6549	0.6493
Score (test)	0.6608	0.6328	0.6588	0.6639	0.6608
Cross Eval	0.6516	0.4705	0.5375	0.6475	0.6493

Table 5: Model Results

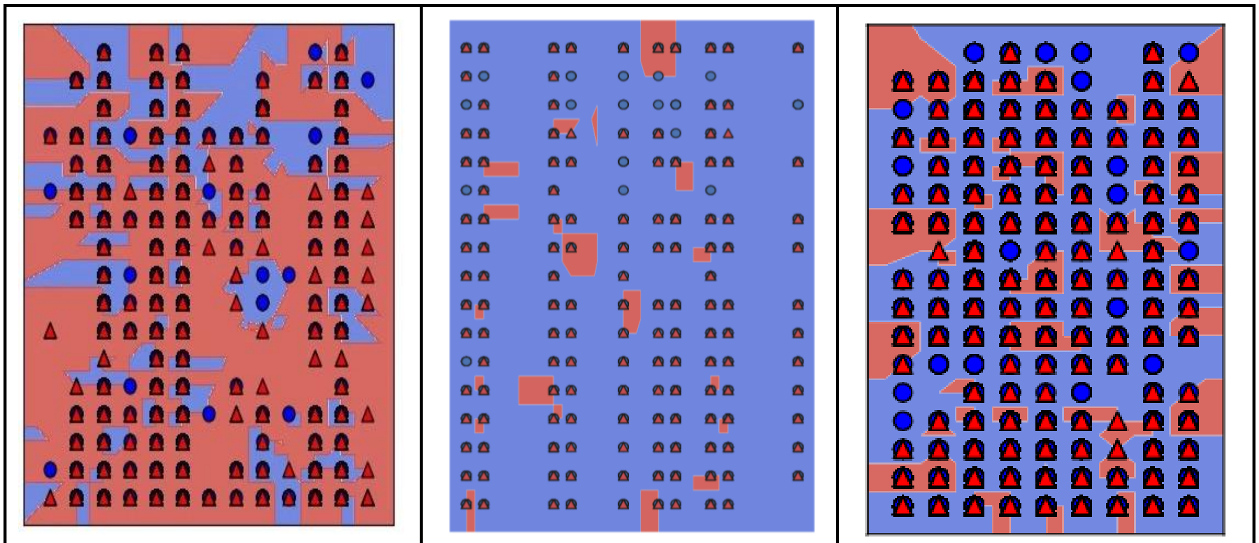
KNN

OpenCritic				
	Precision	Recall	F1 -Score	Support
0	0.34	0.19	0.25	880
1	0.64	0.81	0.73	1726
Metacritic				
	Precision	Recall	F1 -Score	Support
0	0.77	0.99	0.87	3676
1	0.35	0.03	0.05	1082
GameSpot				
	Precision	Recall	F1 -Score	Support
0	0.66	0.91	0.77	1722
1	0.35	0.10	0.15	884

Table 6 : Precision, recall, F1-score for the KNN model for each website.

		OpenCritic		Metacritic		GameSpot	
		A		A		A	
		0	1	0	1	0	1
P	0	171	709	3623	53	1562	160
	1	328	1398	1054	28	797	87

Table 7 : KNN confusion matrix



[OpenCritic KNN (k = 7)]

[Metacritic KNN (k = 7)]

[GameSpot KNN (k = 7)]

Figure 8: KNN Plots

Results

With just two categorical factors, the models did not perform as well as we would have liked them to when predicting a game's review score. The accuracy of each model was negligible and signaled that we needed more factors, at the least, to construct a model that would accurately predict a game's review score. Given the limited amount of data that were available for each review on the sites chosen, we refined our question to that of a binary outcome and applied it to various classification models, though many of these models did not perform much better than the null model (**Appendix**). We wanted to know which classification method would be better to predict if a game will get a score of 80% or better. KNN turned out to be the ‘best’ model relative to other methods.

For the OpenCritic dataset, the model was able to predict a score of 80% or better with about 75% accuracy; there was high precision for predicting games with a score of 80% or better, but low precision for games scoring less than 80%; and the model could correctly identify the actual scores of 80% or better, given the high recall for this group.

The KNN model for Metacritic and GameSpot showed results similar to one another. The accuracy for the model using Metacritic’s data was 10% higher than when using Gamespot’s. The model for both datasets were better at predicting scores less than 80% than those greater than 80%; actual scores of less than 80% were more readily identified than those scores higher than 80%. This is the opposite of what we saw from the OpenCritic dataset, likely because of the differences in the test-train split between the sites given OpenCritic’s tendency to score games more highly than the other sites.

Conclusion

Video game reviews are a popular way to understand if a game is worth buying. Given the disparate mechanisms of reviews and variable scoring between reviewers, our group was interested in understanding if we could predict a game's review score using reviews from popular review sites. We scraped three major websites to obtain the title, genre, platform, and score of 46,958 game reviews between three sites.

A linear regression model performed poorly when predicting the score of a game as a function of gaming platform and genre. Several classification models also performed poorly when predicting if a game would receive a score of 80% or better, but KNN resulted in the best relative model.

KNN models could predict a score of 8 / 80 or better with 63-74 % accuracy between the datasets. OpenCritic data was better for predicting scores and identifying actual scores for games scored greater than 8. Metacritic and Gamespot were better for predicting scores and identifying actual scores for games scored less than 8.

In the future, we would like to get more and continuous factors to create a more accurate linear regression. It would also be useful to create models that hone in specific genres or platforms and predict the score for each respective one to provide a granular insight into future reviews. Given that not all reviews are created equal, we are keenly interested in applying natural language processing techniques to evaluate review text to understand the topics and sentiment that comprises the various reviews and their styles.

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Appendix:

OpenCritic

1. Linear model

Scores(Train)	Scores(Test)	Intercept	Coefficients	Cross Eval. Avg
0.0029	0.0016	89.153	[0.0283,-0.2453]	-0.1

2. Logistic regression

	Precision	Recall	F1 - Score	Support
0	0.11	0.00	0.00	880
1	0.66	1.00	0.79	1726
Accuracy			0.66	1523
Macro Avg	0.39	0.50	0.40	1523
Weighted Avg	0.48	0.66	0.53	1523

3. KNN

	Precision	Recall	F1 - Score	Support
0	0.34	0.19	0.25	880
1	0.64	0.81	0.73	1726
Accuracy			0.60	1523
Macro Avg	0.50	0.50	0.49	1523
Weighted Avg	0.56	0.60	0.57	1523

4. Decision Trees

	Precision	Recall	F1 - Score	Support
0	0.45	0.09	0.15	880
1	0.67	0.94	0.78	1726
Accuracy			0.65	1523
Macro Avg	0.56	0.52	0.47	1523
Weighted Avg	0.59	0.65	0.57	1523

5. SVC

	Precision	Recall	F1 - Score	Support
0	0.44	0.08	0.14	880
1	0.67	0.95	0.78	1726
Accuracy			0.62	1523
Macro Avg	0.56	0.52	0.48	1523
Weighted Avg	0.57	0.62	0.55	1523

6. Linear SVC

	Precision	Recall	F1 - Score	Support
0	0.00	0.00	0.00	578
1	0.62	1.00	0.77	945

Accuracy				1523
Macro Avg	0.31	0.50	0.38	1523
Weighted Avg	0.39	0.62	0.48	1523

Metacritic

1. Linear model

Scores(Train)	Scores(Test)	Intercept	Coefficients	Cross Eval.Avg
0.00035	0.00075	0.2318	[-0.0004, -0.0001]	-0.12

2. Logistic regression

	Precision	Recall	F1 - Score	Support
0	0.77	1.00	0.87	3676
1	0.00	0.00	0.00	1082
Accuracy			0.77	4758
Macro Avg	0.39	0.50	0.44	4758
Weighted Avg	0.60	0.77	0.67	4758

3. KNN

	Precision	Recall	F1 - Score	Support
0	0.77	0.99	0.87	3676
1	0.35	0.03	0.05	1082
Accuracy			0.77	4758

Macro Avg	0.56	0.51	0.46	4758
Weighted Avg	0.68	0.77	0.68	4758

4. Decision Trees

	Precision	**Recall**	**F1 - Score**	**Support**
0	0.77	1.00	0.87	3676
1	0.50	0.01	0.01	1082
Accuracy			0.77	4758
Macro Avg	0.64	0.50	0.44	4758
Weighted Avg	0.71	0.77	0.67	4758

5. SVC

	Precision	**Recall**	**F1 - Score**	**Support**
0	0.77	1.00	0.87	3676
1	0.00	0.00	0.00	1082
Accuracy			0.77	4758
Macro Avg	0.39	0.50	0.44	4758
Weighted Avg	0.60	0.77	0.67	4758

6. Linear SVC

	Precision	**Recall**	**F1 - Score**	**Support**

0	0.77	1.00	0.87	3676
1	0.00	0.00	0.00	1082
Accuracy			0.77	4758
Macro Avg	0.39	0.50	0.44	4758
Weighted Avg	0.60	0.77	0.67	4758

GameSpot

1. Linear model

Scores(Train)	Scores(Test)	Intercept	Coefficients	Cross Eval.Avg
0.0028	0.0038	6.802	[0.0022, 0.0157]	-0.009

2. Logistic regression

	Precision	Recall	F1 - Score	Support
0	0.66	1.00	0.80	1722
1	0.00	0.00	0.00	884
Accuracy			0.66	2606
Macro Avg	0.33	0.50	0.40	2606
Weighted Avg	0.44	0.66	0.53	2606

3. KNN

	Precision	Recall	F1 - Score	Support
0	0.66	0.91	0.77	1722
1	0.35	0.10	0.15	884

Accuracy			0.63	2606
Macro Avg	0.51	0.50	0.46	2606
Weighted Avg	0.56	0.63	0.56	2606

4. Decision Trees

	Precision	Recall	F1 - Score	Support
0	0.67	0.96	0.79	1722
1	0.48	0.07	0.12	884
Accuracy			0.66	2606
Macro Avg	0.57	0.51	0.45	2606
Weighted Avg	0.60	0.51	0.56	2606

5. SVC

	Precision	Recall	F1 - Score	Support
0	0.67	0.97	0.79	1722
1	0.54	0.06	0.11	884
Accuracy			0.66	2606
Macro Avg	0.60	0.52	0.45	2606
Weighted Avg	0.63	0.66	0.56	2606

6. Linear SVC

	Precision	Recall	F1 - Score	Support
0	0.66	1.00	0.80	1722
1	0.00	0.00	0.00	884
Accuracy				2606
Macro Avg	0.33	0.50	0.40	2606
Weighted Avg	0.44	0.66	0.53	2606