Modeling Electronic Arts's Market Success From Game Data

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Abstract

Within the past two decades, the video game industry has erupted into a behemoth which threatens to permanently change the landscape of sports, media, and entertainment. With this growth comes potential for individuals to profit off of investments in publicly traded game companies and publishers such as Nintendo, Sony, and Blizzard. By understanding fluctuations in stock price of these companies in relation to major releases, educated predictions can be made when purchasing and selling stock. We perform analysis to identify trends within the meta data of publisher Electronic Arts's video games through linear, several degrees of polynomial, ridge, and lasso regressions.We test and evaluate our models by predicting stock market changes and sales figures from a dataset of recently released games and comparing the model's prediction accuracy with the true financial numbers.

Introduction

The video game industry has expanded significantly in recent years. [2] In 2016 alone, the Entertainment Software Association reported a 25 billion dollar profit in the sector, taking into account software, DLC and micro-transactions. Hardware sales adds an extra 7 billion dollars to this revenue. [2] As its success increases, so does the interest of third parties seeking to cash in on the profits. However, not every game will be a blockbuster nor can people expect to simply back any company and expect a positive return.From cult classics such as Psychonauts to juggernauts like the recently released Fallout 76, the growing list of commercially failed games proves that the formula for a successful game is not easily derived. With so many different developers, publishers, game genres and other factors, it is difficult for the average person to regularly predict what games will be successful and what games will flop. Market predicting software based on statistical and numerical methods has leveraged popularity for its potential towards a solution for this problem and it will continue to do so as long as there is money to be made.

Since the video game industry now branches into other forms of entertainment such as movies and merchandise, it is difficult to analyze game publisher's total success without placing game sales data in context of their other businesses. To mitigate the the need for studying non-game related data, we reduced the scope of our analysis to Electronic Arts (EA) as they predominately focus on producing video games, have consistent game releases courtesy of their sports series (FIFA, Madden NFL, NHL), and release several large AAA games from series such as Mass Effect, Dragon Age, and Star Wars Battlefront. [9] EA also provides frequent and well structured reports on quarterly earnings, enabling us to compile sufficient data to use for our analysis. [1]

We built models in order to accurately predict trends in EA's net income and stock data given the history of their profits and game releasing schedule. By doing so, we hope to produce a general method that can help estimate trends in stock data to make predictions for other companies.

Regression

Regression analysis makes use of statistics in an effort to estimate relationships between variables. [7] We wanted to use video game data as independent variables and determine what effects they have on our dependent variable (market success of EA) by analyzing patterns between the two over several years. A regression function is derived from training data which is used to predict how our independent variable will act given a testing set of attributes. [7] The different types of regression used to generate our models were linear regression, polynomial regression, LASSO regression, and ridge regression.

Linear regression attempts to model the relationship between variables using a linear function. [7] We used the least squares method for our linear regression. It minimizes the sum of the square of the residuals for each equation generated in order to estimate our unknown parameters for our model. [7] It is an often used form of regression analysis as it can be run simply and often does a good job at identifying trends. Should the model not perform well, more complicated types of regression analysis can be performed.

Polynomial regression attempts to represent variable relationships as nth degree polynomial. [7] We performed this regression with polynomials of degree two, three, four, and five. By fitting a nonlinear model to data, polynomial regression is capable of delineating nonlinear phenomena that linear regression may not be capable of doing. Due to its complexity, polynomial regression is susceptible to overfitting however, and may prove to be less useful than other forms of regression. [7]

Least absolute shrinkage and selection operator (LASSO) regression performs regression analysis in addition to variable selection and regularization. [4] The inclusion of unnecessary features can reduce accuracy of models and lead to overfitting. LASSO regression seeks to remedy this issue by fixing the sum of the absolute values of the coefficients to be less than or equal to a certain value. [4] This effectively removes some of the features from defining the model as their coefficients are set to zero, reducing the complexity of the model. [4]

Ridge regression follows a similar idea as LASSO regression. It intends to simplify the model by reducing the magnitude of the coefficients depending on some penalty variable. [4] Unlike LASSO regression, ridge regression constrains the sum of squares of coefficients rather than the absolute values; it will never set any of the coefficients to zero, merely reduce them. Consequently, it does not choose the features to keep and may not provide as much insight a LASSO could provide. [4]

Data

We gathered our data from three sources, a Kaggle dataset [9], EA's quarterly earnings reports [1] and stock reports [5]. The first dataset features approximately 12,000 video games with the following parameters: Name, Platform, Release Year, Genre, Publisher, North American sales, European sales, Japanese sales, sales in other countries, global sales, average critic score, average user score, number of critics reviewed, number of users reviewed, developer and rating. The dataset features games and consoles from as recent as 2016 with the Nintendo Wii and as far back as the 1985 to the Nintendo Entertainment System. Due to the lack of accessible information, some games had incomplete records which we purged from our dataset to yield a set with a little less than 7000 entries. We then combined all records within the same year to a single datapoint to match with yearly earnings and stocks.

As mentioned earlier,because the dataset contains a wide variety of companies, each with their own influences and revenue sources it is more useful to narrow the scope of our analysis to a single publisher. We chose Electronic Arts (EA) as it is a large publisher who's primary business is video game development. Other companies such as Sony, Nintendo, and Microsoft, while giants

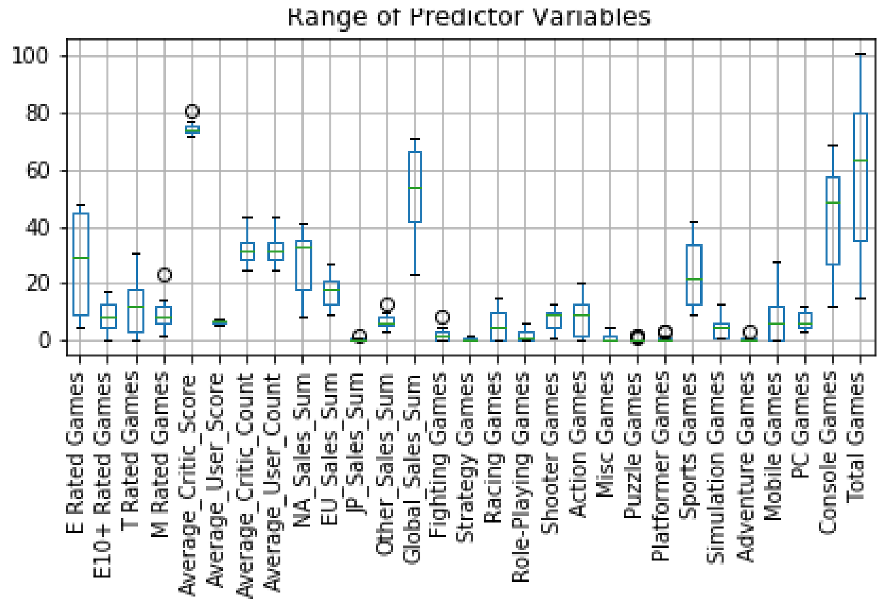

Figure 1: A boxplot exploring the range of our predictor variables.

in the gaming industry, often have business divisions in mediums other than gaming, which may cause a bias in our analysis and our ability to predict its market changes. EA also owns a variety of secondary studios and developers, which should provide an insightful difference in some of our game genre, and sales.

One way of gauging a company's success is by measuring the yields on their earnings report, which in the case of EA, are public and produced quarterly. From EA's earning's reports, we initially analyzed a variety of financial metrics including capital expenditures, operating cash flow, operating income, net income and revenue. We decided to use net income as our target metric since it factors in not only product sales, but also all costs and expenses, which may scale with gross profits. Net income also varies significantly enough year to year compared to other metrics that we can be confident that a model cannot arbitrarily guess based off trends in surrounding data.

Another way of measuring a publicly traded company's success is by measuring their stock value and stock value change over time. Since EA is publicly traded we also recorded stock change over time. Annual change in stock was calculated by summing the monthly changes per year.

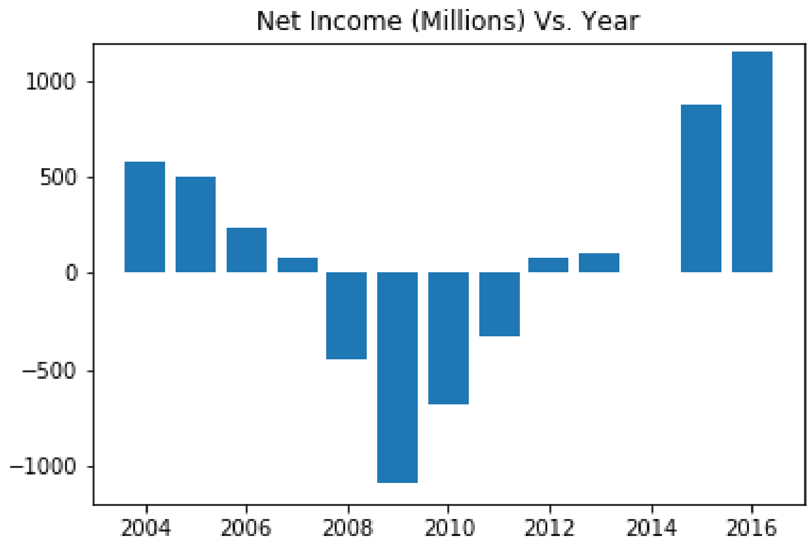

Figure 2: Net Income Graph Vs. Year

Method

Stocks prices can change every minute, so an initial question for our collection of stock prices became: "At what scale do we compile stock data?" Comparing the stock price from the beginning and the end of the year unnecessarily simplifies market fluctuations that may otherwise be evened out. Compiling stock prices each day however, takes in too many of the market's fluctuations. To compromise, we decided on a monthly scope when collecting our stock information. Instead of direct stock prices, we decided to take the stock price at the close of the last day of each month, subtract it by the stock price at the opening of the first day of the month and summate it with ever over monthly change during that year. This gives us smaller values to predict, which may lead to different prediction results than by using net income. We refer to the compiled stock value as the *Monthly Summated Stock Change*.

We used Python's SK-learn regression for its ease of integration with NumPy and Pandas which were used for data processing. Because of our large set of parameters, we built linear regression and polynomial regression models. To explore a range of simpler and complex regression models, we used regression models from degree 2 to degree 5. The stock market has many different variables that can affect how the prices fluctuate, that it can be difficult to identify key features. To combat this we also built ridge and lasso Regression models.

With our limited sized dataset, we used a 75/25 train-test split: more test examples than this risks severely underfitting the models, while fewer test cases

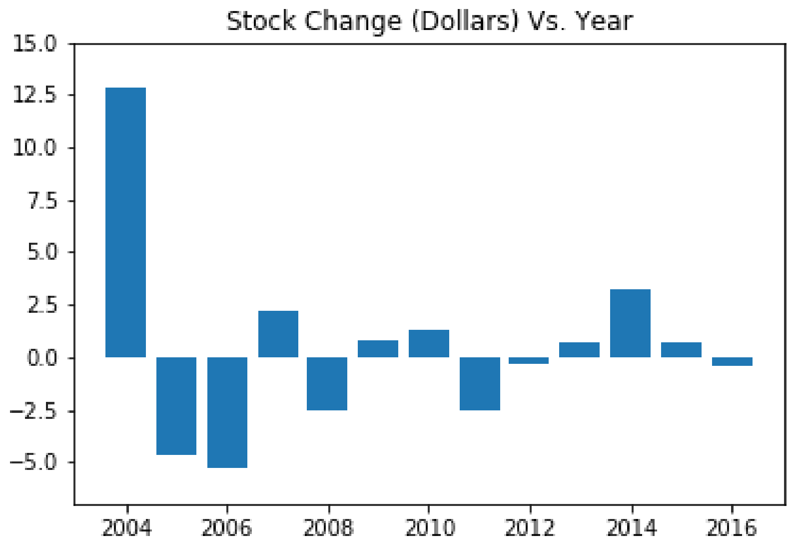

Figure 3: Monthly Summated Stock Change Vs Year

provides less accurate evaluations than our already limited models. Regardless of the split ratio, we faced a shortage of data to use for testing and training with no means of expanding our dataset. With these constraints and the infeasibility of creating mock up data in mind, we decided to randomize the selection of the training and testing sets, run 1000 separate iterations per model and take the average of our evaluation metrics.

Results

We analyze two sets of results, one set for the target variable Net Income and another set for the target variable Monthly Summated Stock Change.

Figure 4 and Figure 5 detail the average mean squared error and the average coefficient of determination calculated from 1000 simulations of each of our models on our target variables. We noticed that due to the random selection of training and testing examples, each individual simulation produced drastically different results, making our final vary with each run. Though unstable, our coefficient of determination consistently remained negative in our calculations, usually ranging from -10 to -200 for our net income variable and -10 to -90 for our Monthly Summated Stock Change. Typically, the coefficient of determination ranged from 0 to 1.0, indicating the predictor variable's "goodness of fit" to predict the variance of its target. Negative coefficients indicate that a model provides extremely poor prediction power that can predict none of its target

	Average R^2	Average Mean Squared Error
Polynimal Deg 2 Regression	-77.36285858	28.51214311
Polynimal Deg 5 Regression	-71.03435269	26.93262666
Linear Regression	-88.62125805	31.97362099
Lasso Regression	-16.79194237	13.21852216
Ridge Regression	-80.19258694	29.46394606
Polynimal Deg 3 Regression	-75.38433253	27.78435858
Polynimal Deg 4 Regression	-73.13502513	27.22224787

Figure 4: Average Coefficient of Determination and Average Mean Squared Error of 1000 simulations for target variable Net Income.

	Average R^2	Average Mean Squared Error
Polynimal Deg 2 Regression	-7.664984036	272870.8198
Polynimal Deg 5 Regression	-8.545020419	282349.4093
Linear Regression	-6.793910883	266159.6955
Lasso Regression	-9.527752497	226641.4741
Ridge Regression	-6.959952475	248131.9784
Polynimal Deg 3 Regression	-8.013939862	275513.5236
Polynimal Deg 4 Regression	-8.291735026	277796.7439

Figure 5: Average Coefficient of Determination and Average Mean Squared Error of 1000 simulations for target variable Monthly Summated Stock Change.

variable variance and that "the mean of the data provides a better fit to the outcomes than do the fitted function" [10].

To get a visual understanding of how these models perform, we took arbitrary regressor models from one of our 1000 iterations and plotted their prediction of our target variables – both training and testing examples against the variable's true values as seen in Figures 6 and 7. From viewing several iterations of these visualizations, we found that our models performed well on training examples but did not generalize well to held out test data with few exceptions. This trend was common across each of our regressor models.

To help explain the models' prediction inaccuracy and their divergence from each other, we analyzed the most five important features from each regression. To calculate predictor importance numerically, we take each predictor's corresponding regressor coefficient and multiply it by the standard deviation of our target variable. By multiplying by the standard deviation, we can standardize our regressor coefficients, which may otherwise be disproportionately sized due to the predictor's units. In Sk-learn, our polynomial regressor models do not compute regressor coefficients. Figures 8 and Figure 9 show the remaining

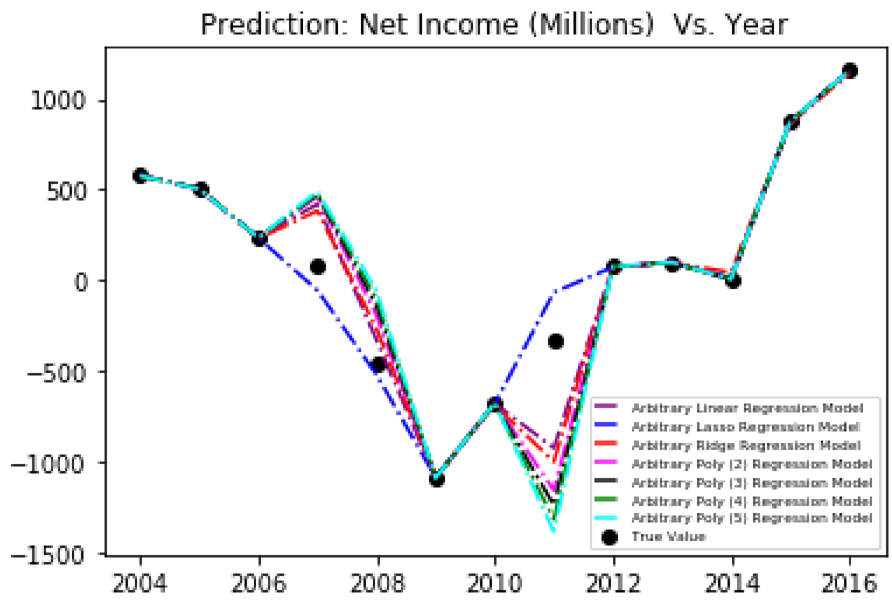

Figure 6: Models Predictions of Net Income Vs True Values.

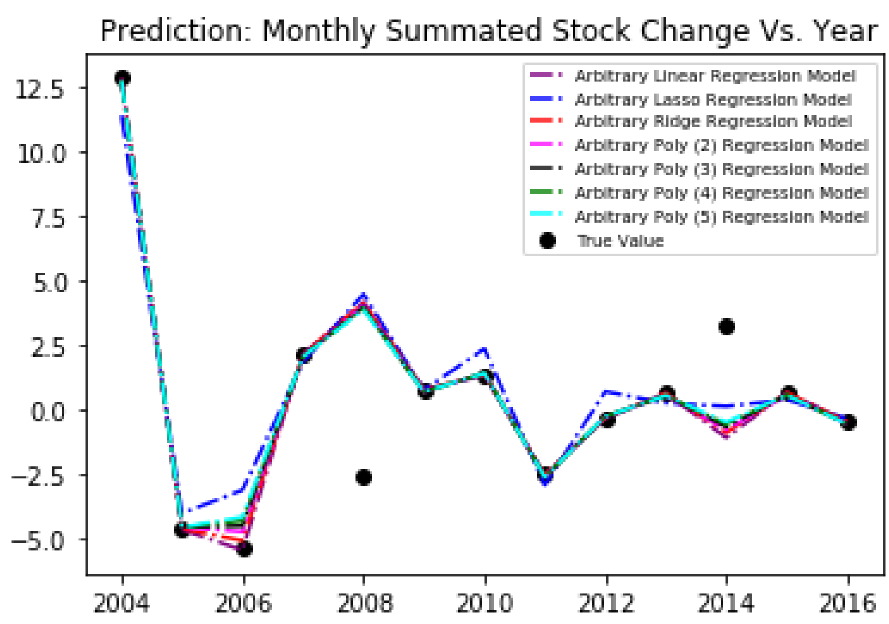

Figure 7: Models Predictions of Stock Change Vs True Values

Linear Regression	Lasso Regression	Ridge Regression
Total Games 6.466652814881089	Mobile Games 5.909133496564416	Total Games 6.301735040170777
Console Games 5.405680096421211	M Rated Games 2.215736251728187	Console Games 4.874175705996267
Mobile Games 4.060410872477054	Console Games 2.1323525625142414	Mobile Games 3.8353197860269295
T Rated Games 2.5326225357445447	T Rated Games 1.5097715841391552	T Rated Games 2.4111145795613704
M Rated Games 2.4137985496709833	Action Games 1.181316755593979	M Rated Games 2.3132761592080566

Figure 8: Most Important Features in Predicting Net Income

Linear Regression	Lasso Regression	Ridge Regression
Total Games 6.466652814881089	Mobile Games 5.909133496564416	Total Games 6.301735040170777
Console Games 5.405680096421211	M Rated Games 2.215736251728187	Console Games 4.874175705996267
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Figure 9: Most Important Features in Predicting Stock Change

models most important features. While we see some common features across our models, we can attribute some of the differences in our model predictions to the differences in top regressor coefficients.

Future Work

While our research showed significantly poor results and a lack of ability to predict EA's market success in both net income and stock price, we have many recommendations for continuing this work. Our first recommendation is to apply our model to different companies and compare outcomes. This may address any unaccounted bias affecting developer specific market sales. Another recommendation is to use a finer scale of financial metrics. Where analyzing game sales from a yearly scope may have generalized some trends, a quarterly scope may help us discover new patterns. Additionally, a quarterly scope provides us with four times as much data as in a yearly scope. Our only hindrance towards pursuing this is that each game was provided with the release year and not the quarter or month. Our next recommendation is to combine some features or drop less useful features to see if they produce new correlations. We would like to see how well we could apply other algorithms such as the simplex method to this topic to understand more about the data. Passing this data into a neural network to perform different types of analysis could also prove beneficial. Word of mouth data is an interesting concept that also incorporates how much "hype" or "buzz" is generated regarding certain topics. [3] Using word of mouth data could provide insight into how successful a specific game or publisher will be. Measuring this data can be tricky, thus it may also prove worthwhile to measure the data as it is produced by gathering, processing, and analyzing data in real-time. Overall lack of ability to get data and analyze at smaller scales was the most limiting factor of our analysis.

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