Genshin Impact Banner Sales Revenue Analysis

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***Abstract*—Genshin Impact, the 3rd highest-grossing mobile game globally, is an action role-playing game by Mihoyo that was launched in 2020. The game has won multiple game awards for consecutive two years. This paper is an analysis of the banner revenue in the Adventure Role-playing video game Genshin Impact in classifying which banners are successful and analyzing the different factors that result in a successful banner. This is done with a dataset of the game's banners and their features taken from Kaggle. The data is then cleaned along with an addition of other features. The banner features we analyzed are the revenue of the banner, the gender of the featured character, whether it is a rerun, a double banner, and the length of banner days. Our exploratory data analysis has shown that double banners, all female characters, and reruns are features that generated the most revenue. With K-means clustering, we have found 20909226 USD to be the revenue marker that separates the "above average" and "below average" labels for classification. The number was found from finding the minimum point of cluster 1 and maximum point of cluster 2, which was added and then divided by 2. Thus the average split point was found. With random forest and SVM, we have found that our model can predict the rating of the banner revenue with a 71-79 percent accuracy. The results of our research have shown that banner features do impact the revenue generated but other features that were not included in our analysis such as character design, pre-marketing of the characters, and player loyalty may also play a part.**

I. Introduction

Gacha games have been around for a long time and so far none have surpassed the success that Genshin Impact has achieved in just 2 years of its existence. The game won the Best Mobile Game award in 2021 and the Player's Voice Award at The Game Awards in 2022. It remains to be the 3rd highest-grossing mobile game globally since its launch with a total of 3.7 billion USD in revenue collected across the App Store and Google Play [1] . Besides the game's lore, music, and outstanding graphics, another important factor that highly contributes to the success of the game are the obtainable characters featured on each banner. Genshin Impact solely relies on making revenue from utilizing its Gacha system. This is done by featuring their new characters and weapons in every version update. Each character and weapon has a rarity ranging from 3-star to 5-star, with 5 being the rarest and most powerful. For instance, Venti is the first featured 5-star character to be released in the game's 1.0 version. As mentioned previously, the game uses a Random Number Generator (RNG) mechanic, supported by a pity system famously known as the "soft pity" and "hard pity". The soft pity starts around 75 rolls which increases the chances of getting a 5-star character drastically while hard pity exists to guarantee a 5-star character in the 90th roll. Without the pity system, it would be difficult to obtain the 5-star featured characters as they only have a 50 percent chance of appearing, and furthermore, it is a mere 0.6 percent chance to obtain a 5-star character. Logically, there are only a few limited reasons why one would conduct in-app game purchases. These reasons include: 1. To obtain one's desired characters 2. To obtain one's desired weapons 3. To collect skins for their favorite characters to wear.

The characters are heavily marketed through social media with official fan art of their design along with their voice lines, story background, and gameplay kit description. To hype the release of a character, they always post video character demos featuring the character and its gameplay mechanics through the company's YouTube channel. This marketing strategy is an effective method to convince users to do in-game purchases for in-game items such as the Blessing of the welkin moon, battle pass, genesis crystals, and other limited item packs. All these purchasable items provide players with the game's currency called "Primogems" mainly used to pull for these characters and their signature weapons. In fact, the game has added a double banner system; featuring 2 limited 5-star event characters at a time. Such a system gives more reasons for players to spend their money.

This research aims to find how the features of a banner affect the revenue it generates. Exploratory data analysis will be conducted along with building several machine learning models. This is to see if the model can predict the revenue class accurately solely from features such as the gender of the 5-star character or the length of days a banner has. Whether the banner is new or a rerun could also be a feature that affects the revenue rating. To measure the success of the game's banner release for every version, we are basing it on the class revenue generated by the banners. The revenue will either be rated "above average" or "below average" which will be a classification label. What is considered above or below average could be found through the help of clustering the data. The aim is to find the average of min and max of two separate cluster points, add them and divide it by two before conducting classification.

II. Related Works

A research study investigates various factors that affect the in-app purchase intention of the Genshin Impact mobile players for instance, satisfaction and loyalty which may also be affected by the perceived value. The results show that satisfaction positively influences the player's loyalty and that loyalty positively influences purchase intention. However, the study also shows that satisfaction itself does not positively influence purchase intention. The study suggests game developers improve the graphics and visuals, and gameplay efficiency, increasing the purchasable items' value for their price and adding new gameplay mechanics to increase their emotional, economic, hedonic, and utilitarian value. It is proven that there is a positive influence of such values on satisfaction and loyalty. Thus it is important to have a loyal player base since loyalty has a very significant positive impact on players' will to do in-app purchases [2].

This article discusses how the second rerun for a Genshin Impact character called Tartaglia was a big hit in Japan and generated as much revenue as Raiden Shogun's first banner, the character whose banners broke many revenue records when it comes to worldwide income. Meanwhile, it was one of the worst day-one revenues in China and is by far, the lowest in Genshin Impact history. The article talks about how Childe's basic appearance, kit design, team compatibility, and gameplay are some of the things that attract Japanese Genshin Impact players into spending on the character instead of following mainstream trends or the meta of the game [3].

Genshin lab created a horizontal bar chart which displays the total revenue generated from each character banner ordered by the total amount and is continuously updated. The chart data is estimated based on the App store data in China Market only. We initially planned to take more revenue data from other sources such as the Playstore for Android as well as other regions however most of the data is locked behind a paywall. This is one of the limitations of our research as the revenue is not from the globally collected data of all countries' app store data and there may be differences in characters' popularity in certain countries which implies that the revenue collected for each banner may be very different for each market [4].

A code created by Salad Yo displays a Genshin Impact revenue table by using a bar plot of the recent banner sales in Genshin Impact up to version 2.7. Through this, we are able to find the most earned revenue and the least earned revenue from the banner sales. Our current data set features such as mixed, rerun, revenue and version date are taken from the kaggle dataset. The revenue dataset has been reviewed and changed according to the China Market App Store data [5].

An exploratory discourse analysis was performed on a community of practice based on Discord, an instant messaging platform where numerous themes in players' discussions have been observed; such as their criticism to the gacha's probability system, sexualization of female characters, and opinions regarding monetization and the game's developers. These diverse themes show the potential that communities of practice have in allowing game developers to better understand their player base beyond the game's app ratings and reviews [6].

A study was done on how genders are represented in the game Genshin Impact, which is one of the games that contain a lot of repetitive linguistic input. The dialogues of the game were examined through a corpus-assisted approach in order to see how female and males are represented. Men are found to be the receivers of violent actions while women were associated with supernatural powers, fame and successful careers. The absence of violence and sexualization showed that there were better gender representations compared to past games. The way genders are represented in the game is important according to the research since it can negatively impact the behaviors of individuals by corrupting their perspectives on it [7].

A discussion was done on how the implementation of artificial intelligence backed with the Fuzzy Tsukamoto method may help new players select proper artifacts for them to choose. The implementation is done with the Python language [8].

A study to determine the impact of product quality and customer value on customer loyalty in purchasing items in the Genshin Impact game. They analyze the data by doing a reliability and validity test, a classical assumption test, and a hypothesis test. The results of the t-test showed that there was no significant effect between product quality partially on customer loyalty, whereas customer value had a significant effect on customer loyalty. Second, the f-test results show that product quality and customer benefits simultaneously affect customer loyalty [9].

Research of the positive impact in the long-term and negative influence in the short-term impact of COVID-19 on the Chinese game industry. This research uses regression to confirm a linear relationship between the severity of COVID-19 and the performance of the gaming industry. The virus was found to have a negative impact on the entire gaming industry in China at the beginning of the COVID-19 outbreak, but government policies influenced by COVID-19 have positively impacted the gaming industry in China [10].

This study aims to determine the influence of the game's music on the gaming experience of Genshin Impact. This study uses experimental and qualitative research methods. Data analysis for both methods is performed using the SPSS application and is first codified. Based on the results of the experimental and qualitative data analyzes conducted, the authors conclude that musical variables influence game experience variables [11].

This study analyzes the design of the game's open world map, the elements used in the game map to allow players to immerse themselves in the game map, the gameplay of the game, and the added card draw system that makes Genshin Impact popular. It is concluded that the Genshin Impact game is extremely popular due to its novel design and rich and diverse gameplay methods [12].

This study examines how online gaming addiction and perceived value influence in-game purchase intentions and mediate loyalty among Genshin Impact players in the Philippines. Researchers used Jamovi, Statistica, and SPSS Hayes PROCESS to interpret and analyze the results of the collected data. The results show that online gaming addiction and perceived value, including playfulness, connectivity, flexibility of access, reward, and superior value sub variables, significantly influence loyalty in Genshin Impact games. In addition, online gaming addiction has a significant impact on in-game purchase intentions [13].

The purpose of this study is to examine the effect of gamers' consumptive behavior on gacha purchases in the Genshin Impact Game. The research method used is a quantitative type with the accidental sampling technique. The coefficient of determination (R2) results shows that 74.5 percent is influenced by the consumptive behavior of the players, while the remaining 25.5 percent is contributed by other factors that can be explained by other variables outside the model [14].

The aim of this study is to find differences in how experienced and new players approach game reward systems and how their relationships with those systems are affected. In addition to a great gaming experience, the focus is specifically on the game's economic system. This is done through a mixed method approach that uses aspects of both formal analysis and autoethnography. It was concluded that at a certain point the game no longer concerns itself with rewarding players adequately shown by the game offering less and less goals to work towards for players, which leads to the lack of meaningful content [15].

III. Dataset and Preprocessing

The dataset we have chosen will be regarding how much revenue the game has made from all the banners in the past 2 years since the game was released. The data includes the version when the banners were released, the name of the version, the banners' start date along with the end date, the 5-star characters that were put in the Gacha banners, whether the banner contains a rerun of a character, whether the 5-star characters are all male, female or a combination of both, whether it is mixed meaning it contains multiple 5-star characters instead of just one, the amount of revenue in US dollars produced by each banner, how many days each banner lasted for, and finally the average revenue it creates per day.

Table I displays the top 5 most recent banners. The data has been cleaned and furthermore, we have added extra data sets from reliable external resources like Genshin lab and Genshin wiki. This was because the data we took from Kaggle was a bit outdated as it was missing the current banners' revenue details and we did not have much data to work with. Considering how new the game still is, it is to be expected that our dataset is relatively small but it is still sufficient enough for us to conduct multi-staged data cleansing and utilize it to build predictive models using supervised and unsupervised learning. We then decided to update the dataset further by inputting data such as the revenue and length of days of each banner until version 3.2 banners since the data we obtained from Kaggle only had it up to version 2.7.

Currently, we have around 39 sets of data regarding the number of banners that have been available since version 1.0 to 3.2. The previous data before it was cleaned was still missing some data or had N/A values. Steps we went through after updating the data from the excel spreadsheet, we also calculated the mean, minimum, and maximum of the sales revenue. Additionally, we also added the gender label for each banner with 0 meaning all the 5-star limited characters featured were male, 1 being all female, and 2 means one of them is female and the other male.

Here in Table II shows all the data types of our collected data with the help of pandas by reading the excel file sheet and putting it into a data frame.

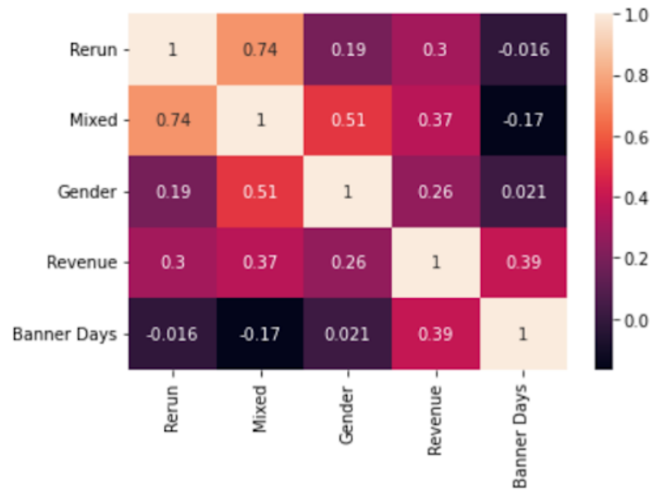

Fig. 1. Correlation matrix of the banners.

We also included a correlation matrix in Figure 1 as part of our exploratory data analysis which displays the correlation coefficients for different variables. We are interested in seeing whether the variables are completely uncorrelated, have a weak correlation, strong correlation, or have a perfect correlation. When r = 0.9 or 1 (positive or negative), it indicates that there is a perfect correlation. Meanwhile r = 0.5 to 0.9 (positive or negative) means there is a strong correlation. If r = 0.1 to 0.5 (positive or negative), it shows there is a weak correlation. Finally if r = 0 or 0.1 (positive or negative), it strongly means there is no correlation at all. From the heatmap, we can see that there is a strong correlation between the variable Mixed and Rerun as the r is 0.74. There is also a strong correlation between the Gender variable and the Mixed variable since the r = 0.51. The variable revenue, when matched with other variables such as Rerun, Mixed, Gender, Revenue, and Banner days, displays that there is still a correlation among them however it is considered weak. The fact that there is still some correlation says a lot as we can still look into it and earn an interesting insight. It is to be remembered that the variables Rerun, Mixed, and Gender are only limited to certain integers such as 0, 1, and 2 which may have affected the correlation between the variable revenue since those numbers without labels stated will not make sense alone.

TABLE I
TOP 5 MOST RECENT BANNERS DATASET

Ver.	Ver. Name	Start Date	End Date	5 Star Char.	Rerun	Mixed	Gender	Revenue	Bnr Days	Avg Revenue per day
3.2	Akasha Pulses, The Kalpa Flame Rises	2/11/22	18/11/2022	Nahida Yoimiya (2nd Rerun)	2	1	1	$34,017,290	17	$2,001,017.06
3.2	Akasha Pulses, The Kalpa Flame Rises	18/11/2022	6/12/22	Tartaglia (3rd Rerun) Yae Miko (2nd Rerun)	1	1	2	$18,437,409	19	$970,389.95
3.1	King Deshret and The Three Magi	28/09/2022	14/10/2022	Cyno Venti (3rd Rerun)	2	1	0	$19,052,023	17	$1,120,707.24
3.1	King Deshret and The Three Magi	14/10/2022	1/11/22	Nilou Albedo (2nd Rerun)	2	1	2	$15,731,680	17	$925,392.94
3	The Morn A Thousand Roses Bring	24/08/2022	9/9/22	Tighnari Zhongli (3rd Rerun)	2	1	0	$19,068,372	17	$1,121,668.94

TABLE II
DATASET DATATYPE

#	Column	Non-Null Count	Dtype
0	Version	39 non-null	float64
1	Version Name	39 non-null	object
2	Start Date	39 non-null	object
3	End Date	39 non-null	object
4	5 Star Characters	39 non-null	object
5	Rerun	39 non-null	float64
6	Mixed	39 non-null	object
7	Revenue	39 non-null	float64
8	Banner Days	39 non-null	float64
9	Avg Revenue/Day	39 non-null	float64
10	Featured 5 Star Gender	39 non-null	float64
11	Revenue_Class	39 non-null	object

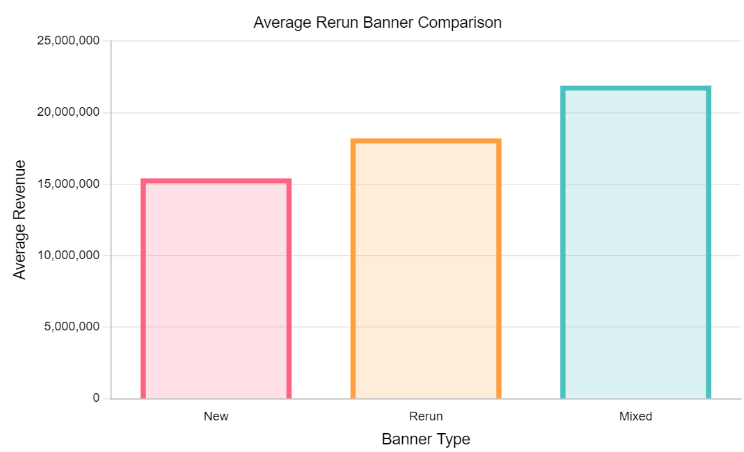

Fig. 2. Average revenue comparison between the rerun banner types.

We calculated the average revenue of all banners categorized by the gender of the featured 5-star characters shown in a bar chart in Figure 2. The first category is where all the featured 5-star characters are male and when averaged, the revenue is around 14,900,569 USD. The second category is where all the featured 5-star characters are female and when averaged, the revenue is around 18,765,292 USD. The last category is where all the featured 5-star characters are a mix of female and male which resulted in an average revenue of 20,770,147 USD. The average revenue is plotted in a bar graph to see which banner categorized by gender generated the most revenue. From the results, we can conclude that a mix of male and female characters in a banner generated the most.

The results, however, may be unfair since most of the all-female/male banners were single banners. It contains only one featured 5-star character meanwhile the mixed gender undoubtedly contains 2 featured 5-star characters. Thus we did another comparison between the double banners only that contains all male, all female, and lastly, a combination of

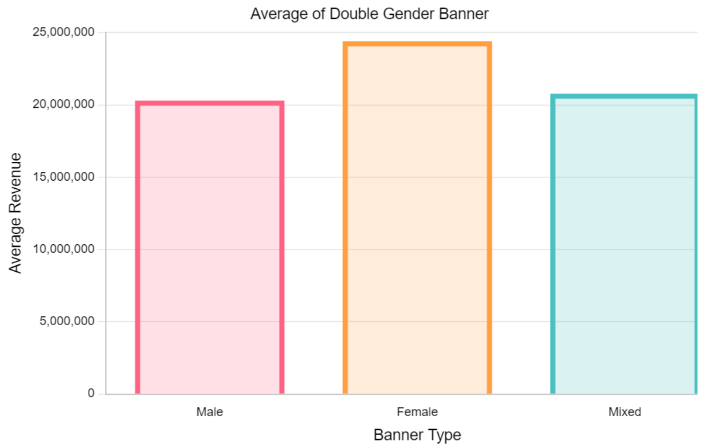

Fig. 3. Average revenue comparison between the gender of double banner.

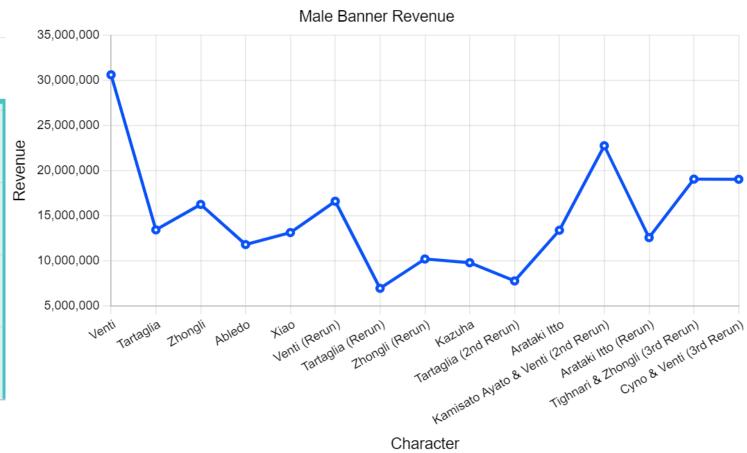

Fig. 4. Revenue comparison from the 5-star male banners.

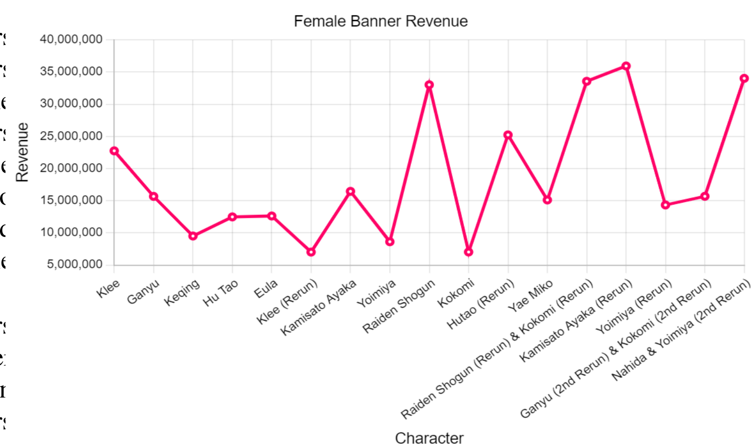

Fig. 5. Revenue comparison from the 5-star female banners.

both genders. The result of the revenue of the average banners can be seen in Figure 3. Surprisingly, the all-female banners generated average revenue of 24,398,163 USD and are the most out of the 3 categories. Meanwhile, the mixed banners come second, and the all-male banners generated an average of 20,295,950 USD not that behind the mixed banners. It is to be noted that the all-female double banners generated around 4 million USD more than the all-male and mixed double banners.

When comparing the performance of the single banners against the double banners without accounting for any other features, it is clear that the double banners are successful in increasing revenue by a large margin. The double banners averaged a revenue of 21,821,420 USD meanwhile the single banners only averaged a revenue of 16,834,930 USD.

Another feature to be tested is the Rerun of a banner. It is classified into 3 categories. The "New" category is when it is the first time the featured 5-star character makes an appearance in the game's banner history. The "Rerun" category indicates that the featured 5-star character has made an appearance at least once in the past. The "Mixed" category indicates that the banner contains a new 5-star character and a rerun of a past featured 5-star character. Interestingly, the "Mixed" category generated the most revenue, an average of 22,500,000 USD. Second, comes the "Rerun" category of 17,000,000 USD with the last being the "New" category generating only around 15,500,000 USD on average per banner. The gap between the "Mixed" and the rest is quite notable as seen from the bar graph. It can be concluded that a combination of a new character and a rerun character is considered to be the most successful.

In Figure 4, all the banners that contain only featured 5-star male characters are plotted in a line graph. It can be seen that the trend has mostly been going down with none of the banners surpassing the revenue performance of the first featured 5-star male character, "Venti".

In Figure 5, which contains featured 5-star female characters only is plotted in a line graph for comparison. It can be seen the revenue fluctuates often and leans towards an increasing trend. The all-female banners are doing better than the all-male banners in terms of revenue history. Although there is not much data to evaluate the performance of the mixed banners' average revenue optimally, the banners have consecutively performed well 3 times in a row. It is an indicator that a combination of both genders may be the most optimal in generating above-average revenue.

IV. Methodology

We wrangled the data set in excel and used Sklearn to train the data as it provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, and clustering. We have implemented several machine learning models ranging from unsupervised and supervised in order to compare which is the best to use for our case.

We have decided to use 3 machine learning models, two from supervised and one from unsupervised learning. Supervised learning is used to classify data or make predictions. We are using supervised learning since we want to build a model that can predict the revenue class of the banners from some features. Unsupervised learning is often used to understand relationships within datasets and find hidden patterns in unlabeled data. Since we want to identify what possible combination of features makes a banner successful, clustering will be done. For unsupervised learning, we are performing K-means clustering on our data set. While for supervised learning, we are using SVM and Random forest to do Classification.

A. Clustering

Clustering is needed to see how the banners are clustered based on the similarities of their features. The features used to group them into clusters are banner days, revenue, mixed, rerun, and gender. Another objective is to find the amount of revenue that separates the two clusters. This can be achieved by using K-means clustering. We can find the minimum revenue found in the first cluster and the maximum revenue found in the second cluster. It can then be added and divided by two to find the border that separates the two clusters. This new value is essential to help us determine the revenue value that separates "Above Average" and "Below Average". Without it, it would be difficult to create classification labels for our supervised learning model.

B. Classification

The goal of using classification models is to see whether they can be trained to predict if the revenue is classified as above average or below average based on the features given such as gender, banner days, mixed, and rerun. Whether the model is considered successful or not will depend on the accuracy score of the model. If the score is above 0.70 then the model is successful enough in predicting the revenue class. To perform classification, we need a classification label called Revenue Class where the revenue can be classified as either "Above Average" or "Below Average". The features used for classification are banner days, gender, mixed, and rerun. The first model we used is SVM or also known as Support Vector Machine and several settings were used to see which setting leads to the best accuracy score. We have tried linear and rbf for the kernel, as well as changing the C, random state, and gamma settings to find which is best suited for our model. The second model we used is the Random Forest Classifier using the same features used for SVM. It is also used to predict the same classification label, "Revenue Class". The reason behind using two different classification models is to see which model performs the best in predicting the revenue class label based on the 4 features mentioned. Afterward, we will summarize our findings and evaluate which model is the best for our data set.

C. Evaluation Method

Evaluating model performance with the data used for training is not good nor is it acceptable since it can easily generate overoptimistic and overfitted models. Therefore it is crucial to pick an evaluation method to put our model into the test and ensure our model does not overfit or underfit.

Since we have a small data set of 39, the ideal choice to evaluate our classification model is using the k-fold cross-validation technique. The dataset will be split into k equally sized subsets called "folds". One split subset will be the testing set and the remaining folds are used to train the model. In this case, there will be 15 folds or k=15. This technique will be used on both SVM and Random Forest, and print the scores out. The mean of the scores will then be computed. The settings of the classifier such as the type of kernel for SVM can be tinkered with manually to find the best possible outcome.

$$s = \frac{(b-a)}{max(a,b)} \tag{1}$$

The evaluation method used will be the Silhouette Coefficient or Score as a metric to calculate the goodness of a cluster. This will only be performed on the K-means clustering since the purpose is only to see how well the data points are clustered only from the score. The amount of clusters specified for K-means is only 2. The elbow method is also used to determine the ideal number of clusters based off our dataset.

V. Result and Analysis

A. Supervised Machine Learning

The cross-validation mean result is higher when the kernel is set to linear compared to rbf. When the kernel was set to rbf, the cross-validation score mean resulted in 0.67. The kernel is then set to linear which produced a mean score of 0.79. For the settings, the gamma is set to 2.0, and C is set to 20.8 with a random state = 1 during the entire testing process. The settings for the Random Forest classifier are different, however, where max depth is set to 5 and the random state is set to 1. The number of folds is also set to 15 to make the comparison as equal as possible. The random forest classifier produced a mean score of 0.71 when k= 15. Both of the scores produced by SVM and Random Forest is above 70 percent and thus our classification model is considered successful in predicting the revenue class labels. When the number of cross folds is set to below 10, the score was below 0.60 for both SVM and Random Forest. This is how in the end, the amount of folds is set to 15 as it produces the best cross-validation result on average.

B. Unsupervised Machine Learning

For K-means clustering, the clusters are plotted as seen in Figure 6. The elbow method and the KneeLocator suggested 2 clusters for our dataset. Since that is the ideal number of clusters to have, we set n= 2 where n is the number of clusters. Both figures showed that the data can be clustered properly in two clusters and achieved a silhouette score of 0.68. Since there is a gap between the minimum revenue point in cluster 1 and the maximum revenue point in cluster 2, we printed the data points of the revenue. The minimum revenue point in cluster 1 was found to be 22750080 USD. The maximum revenue point in cluster 2 was found to be 19068372 USD. These two numbers are then added and divided by two which resulted in a revenue of 20909226 USD. With this number, we have found the value to determine if revenue is successful or not. If the revenue number is above 20909226 USD, then we can create a label for classification named ”Above Average”. If the revenue number is below 20909226 USD, then the label can be called ”Below Average”. This method is better than using the mean of the total banner revenues due to the size of the data set.

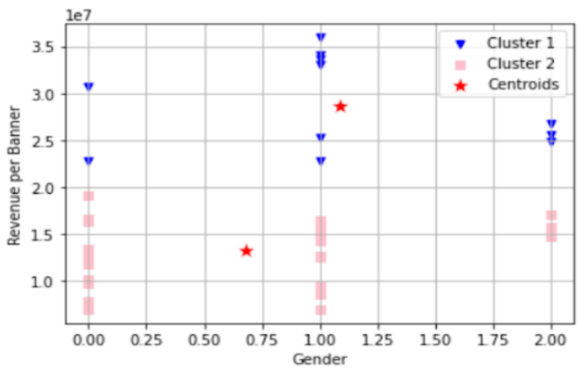

Fig. 6. K-means clustering of the gender banner and its revenue.

In Figure 6 shows how the Revenue per Banner against Gender as the x-axis are clustered. Interestingly enough, there are more of the individuals from cluster 1 displayed in the female gender. This means that when a banner character that is featured is female, it has so far produced the most revenue compared to if the banner is all male characters or a mix of both. If there were more data where the gender of the characters is a mix, it may possibly generate more revenue compared to when the gender of the characters is all male.

VI. Conclusion and Future Work

Clustering using K-means has contributed to determining a value to classify what is above average and below average revenue-wise. This revenue value is found to be 22750080 USD where anything above will be determined as successful and vice versa. This finding has allowed us to conduct supervised learning: Classification using SVM and Random Forest. Both models have been successful in predicting the Revenue Class labels. When put into the test of labeling unseen data with “Above Average” and “Below Average”, it has a cross-validation score of 0.71 to 0.79. However, to produce that outcome, with SVM, the kernel needs to be linear and not rbf. With rbf it outputs a score of 0.67 which would be below 0.70 and may not be a good predictive model to rely on. It is also recommended to use a higher amount of k folds if possible as it increases the cross-fold mean scores since more data is used for training. Thus it can be concluded that the banner features can predict whether it is above or below 22750080 USD by a score of 79 percent. Features such as gender, mixed, and rerun does affect the revenue with gender being the biggest factor as seen from the clusters. In the future, we plan to re-conduct this research since there would be more datasets to work with. We also recommend furthering our research by using datasets of other countries’ Genshin Impact IOS market revenue banners with the same methodology. Another suggestion is to analyze how the amount of likes received by the character video demo or posts featuring an upcoming 5-star character affects the banner revenue.

Supplementary Codes

The code for this paper can be accessed through the following link: https://github.com/Pandalmation/Genshin-Banner-Revenue-Analysis/tree/main/Code.

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