Liquipedia Project

Aditya Jain
Universität Passau
Passau, Bavaria, Germany
jain05@ads.uni-passau.de

Mustafa AlShdaifat
Universität Passau
Passau, Bavaria, Germany
alshda01@ads.uni-passau.de

Ajay Kesarwani
Universität Passau
Passau, Bavaria, Germany
kesarw01@ads.uni-passau.de

ABSTRACT

Liquipedia is an E-sports wiki for online games, which gives information about teams, players, tournaments, and more in one place. In this project, we researched how do the active years, transfers, and achievements affect the overall popularity (Twitter followers) of the player in three games namely "PUBG", "Fortnite" and "Counter strike". We concluded that the active years and transfers do affect the overall popularity (Twitter followers) of the player, but negatively. For all three games, we found that achievements and transfers had a negative impact on the follower count, which means players lost followers generally.

1 DATASET & PREPROCESSING

Scraping data was the first step toward harvesting data and went through two stages from two different websites namely "esport" [7] "Socialblade" [7] and "Liquipedia"[3] . We have used many tools for scraping and analysis like Numpy, Pandas, Selenium, BeautifulSoup, Matplotlib [1, 4–6, 8].

1.1 Scraping data from Esportsearnings

From "esports-earnings"[2], we have scraped over 1000 players data for each game in the 3 games we selected, namely PUBG, counter strike and fortnite.

1.2 Scraping data from Liquipedia

From "Liquipedia", we scrape some information about the players, such as twitter handles, achievements, transfers and earnings. This information helps us to scrape data from the social-blade website since we need the Twitter to handle to retrieve information about a player using his/her Twitter handle name. Figure 1 shows a figure captured from "Liquipedia"[3] website showing the information which can be extracted from this page such as achievements, transfers, earnings, birthday etc.

1.3 Scraping data from Socialblade

On this website there are around 3 years of social media interaction database, such as Twitter, so we can get Twitter Statistics and Summary, a lot of data can be harvested from this website such as Twitter followers gained or lost, gained tweets or gained likes.

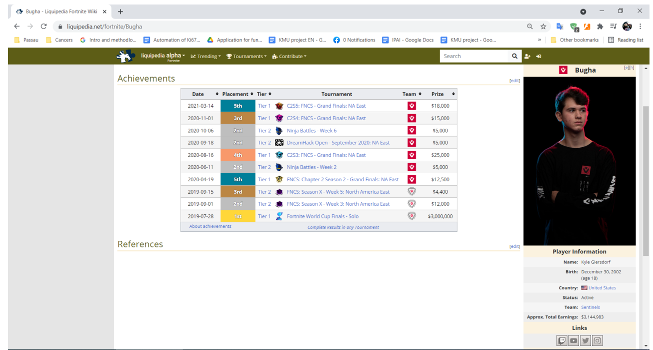

Figure 1: Player profile from Liquipedia website for player Bugha (https://liquipedia.net/fortnite/Bugha).

In this project we are interested in the number of followers as an indicator of popularity, therefore we can correlate this information with transfers and achievements, and study how this affects the popularity. In Figure2 we show a screenshot from the "Socialblade" website that contains information for a player called "Bugha" see Figure 2.

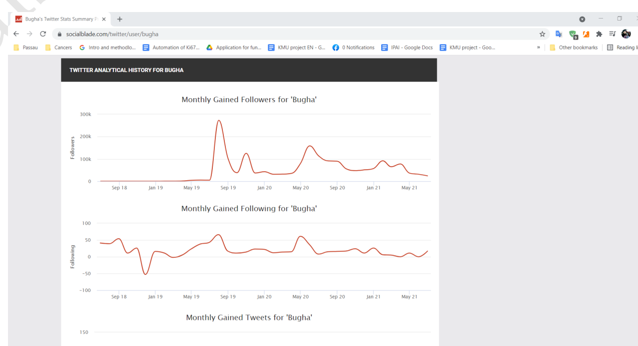

Figure 2: Player profile from Socialblade website for player Bugha showing the twitter interaction in month duration (https://socialblade.com/twitter/user/bugha).

2 ANALYSIS METHODOLOGIES

2.1 Pearson Correlation Coefficient

For our first analysis, we use the Pearson Correlation Coefficient to find a correlation between our data sets, which have been divided into two parts. The Pearson Correlation Coefficient is a ratio between the co-variance of two variables and the product of their standard deviations. It essentially gives a normalized measurement of the co-variance, and thus, the result is always a value between -1 and 1. It helps to find how strong a relationship is between data. “1” indicated a strong positive relation, “-1” indicates a strong negative relation, and “0” indicates no relationship.

Correlation between Achievement Data and Twitter Followers

In the first part, we find the correlation between the Achievements of a Player and the Twitter followers they have gained based on these achievements. We take the achievements from the scraped data and assemble them in a data set, which contains the following:-

- PlayerID (Player Name)
- Achievement Date
- Twitter Followers

This data set is created after cleaning and structuring the data in many ways. First, we start by gathering the achievement data, specifically the achievement dates and the player for whom we fetch this data, and store it in a list. Next, we do the same and fetch Twitter data for the same player and store it in a list as well. Next, we need to change the dates and edit them in a common format, and to generalize this, we convert the dates from both, the achievements, and the Twitter data, in a “Month-Year” format.

This helps us in the next step, as we find the cross-section between our two lists, by performing an intersection between the two lists, which returns the month in which the player played a certain tournament and the followers he gained for that month. This closely gives a specific number of followers the player gained, during that time, which includes the time from the promotion of the event, the actual event, the outcome, and the result of that outcome. So, if a player loses this tournament, he might gain fewer followers overall, compared to when he wins the tournament, resulting in a higher gain of followers.

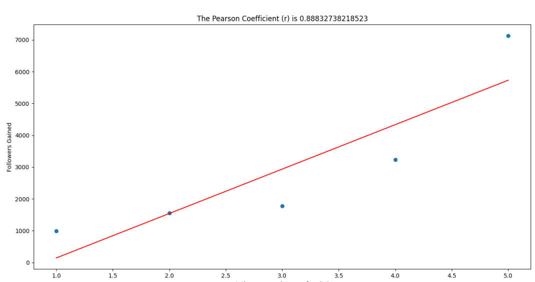

Figure 3: Plotting the values using the Pearson Correlation

Once we fetch these data sets, by performing an intersection, we store this in a list and finally plot the graph. For the plot, we have our dates on the X-axis and the followers gained on the Y-axis. This is also labeled for ease of understanding. Next, we find the correlation values by using the list we acquired. But here, we face an issue, specifically with the dates. The dates are in a Date-time format in Python, which cannot be used directly in the formula to find the correlation value. Therefore, we normalize the date values by assigning the dates as single integer values, based on the count of this list. For example, if for “Player 1”, we have a total of 9 values in the intersected list, then the dates will be from the range of 1 till 9. This helps us calculate the correlation coefficient easily and plot the values on the graph as shown in Figure 3.

For the plot, with the X-axis and the Y-axis defined, we now calculate the values and use a Poly fit to help us visualize the overall relationship between the 2 data sets much more easily. Poly fit is a linear line that is plotted on the graph to show a strong. It returns the coefficients of a polynomial of degree that is the least-squares fit to the data values y given at points x. Once the graph is plotted, we can visualize the following as shown in Figure 4:

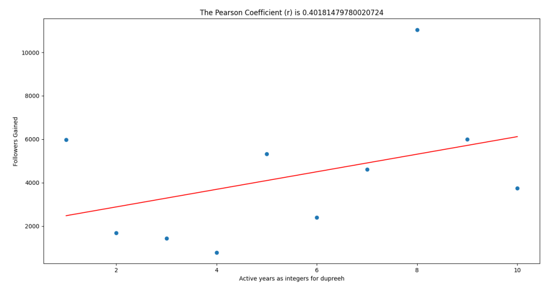

Figure 4: Positive Correlation for Achievement and Twitter Data

The graph in Figure 4 shows us a positive correlation, which is above 0, with r = 0.401. The red line indicates the Poly fit that fits based on the data set values to help visualize the correlation much easily. From this graph we can conclude that the achievement and the followers for this player are directly proportional to each other, meaning that with more achievements and by participating in more tournaments, the player saw an overall gain of Twitter followers.

Correlation between Transfer Data and Twitter Followers

In the second part of the analysis, we take the same twitter data from our scraped data set and take the Transfer data of players as well. The transfer data consists of two dates, the date of transfer, basically, the date when the player joined a team, and the date of termination when the player left a team. Along with this, we have the Team Name, which the player joined and played for during that time. We gather all this data into a list and follow the same steps as mentioned above.

We begin with creating two lists, the first with the transfer data and the other with the Twitter data. The transfer data contains the dates of the transfer as well as the teams and the player ID, whereas the Twitter data contains the same details, the followers, and the dates for the player. We then format the dates into a date-time format, the way we did for the previous data sets, and convert them into a “Month-Year” format. Then, we find the cross-section between these two lists, performing an intersection on the data sets (list), and find all the common dates where the player transferred to another team and the followers gained for it.

Once we fetch these data sets, by performing an intersection, we store this in a list as well and finally plot the graph again. For the plot, we have our transfer dates on the X-axis and the followers gained on the Y-axis. Next, we find the correlation values by using the list we acquired. But here, we face the same issue, specifically with the dates. The dates are in a Date-time format in Python as mentioned above, which cannot be used directly in the formula to find the correlation value. Therefore, we normalize the date values by assigning the dates as single integer values, based on the count of this list, like the way we did it for the achievement data, similar to Figure 3.

Here, the intersection of the lists returns us the date of the transfer for the player and the followers he gained for it. *We consider the period, a month for this approximately as well, because this includes the time from the announcement to the actual transfer and the news after the transfer. This gives us a good figure of the followers that the player gained during this period of publicity to find out how many followers he gained or lost to form a negative or positive sentiment, depicted by the correlation.*

Once we fetch these data sets, by performing an intersection, we store this in a list as well and finally plot the graph again. For the plot, we have our transfer dates on the X-axis and the followers gained on the Y-axis. Next, we find the correlation values by using the list we acquired. But here, we face the same issue, specifically with the dates. The dates are in a Date-time format in Python as mentioned above, which cannot be used directly in the formula to find the correlation value. Therefore, we normalize the date values by assigning the dates as single integer values, based on the count of this list, like the way we did it for the achievement data. For the plot, with the X-axis and the Y-axis defined, we now calculate the values and use a Poly fit here as well to help us visualise the overall relationship between the two data sets. Once the graph is plotted, we can visualise the following as shown in Figure 5.

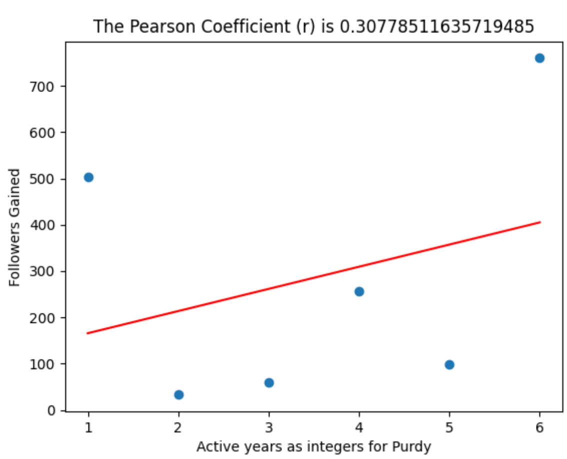

Figure 5: Correlation between Transfer and Twitter Data

This graph in Figure 5 shows us a strong negative correlation, which is below 0 and closer to -1, with r = -0.871. The red line is the Poly fit for this data, showing us a downward linear fit. From this graph we conclude that the transfer to a team and the followers for this player are inversely proportional to each other, meaning that with the transfers to another team, the player saw an overall loss of Twitter followers.

1.2 The Box and Whiskers Plot

For our Second Analysis, the relationship between transfer against the Twitter followers and achievement against the Twitter followers needs to be determined. Therefore, the Box and Whisker Plot[1] is used. In order to use this plot, we first need some data sets. Therefore, we collected Twitter follower data for all players from the scrapped file, basically for two categories:-

- Achievement Details
- Transfer Details

1. Achievement details:- When a player is active and he is playing a tournament, we store the gain in Twitter followers for that player in that month.

For e.g. a player named "Park Jung-young" with an id "Loki" played a tournament named "PUBG Warfare Masters 2018 - Pro Tour" on "2018-06-13" and tournament named "PUBG Nations Cup 2019" on "2019-08-11". So the **Twitter followers gain data during tournament** [2] for the entire month of June 2018 and August 2019 stored and used for analysis.

The above process is repeated for each tournament and the Twitter follower data is collected for that month in order to find any relation between them.

For all players, we collect this data and then we plot them with the help of a box and whiskers plot. We used the notches in the box plot to try to find the popularity of that player based on Twitter followers data and find whether a tournament a player has played had any impact, like increase, decrease or uniform followers gain count.

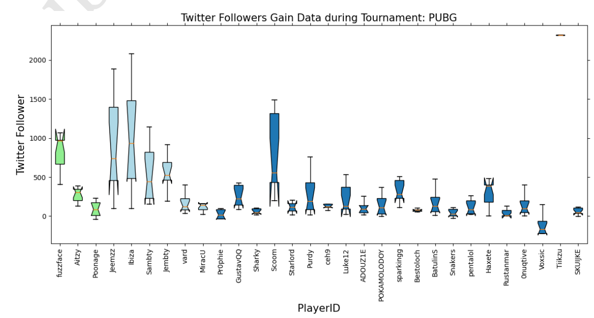

Figure 6: Twitter Follower Gain Data during Tournament for PUBG

The Figure 6 shown is for the game "PUBG" which tells the behaviour during Tournament for 30 players. Here, We found that 22 players lost their followers, 7 players gained followers while 1 player didn't have any effect on Twitter follower data.

For e.g. first player id "fuzzface" notch is pointing upwards, which means that the more he plays the tournament the more he gains Twitter followers while it is opposite for fourth player id "jeemzz",

[1]Box and Whisker Plot: A box plot that displays the data-sets on five parameters, e.g. Higher value, 1st Quartile, median, 3rd Quartile, and lowest value

[2]Twitter followers gain data during tournament: Generally, followers have the information a few days before about the upcoming tournament, telling them which players are going to play, so they follow them accordingly. Also when a tournament finishes, followers try to follow those players who played that tournament. As this ripple is generally seen a few days before and after the tournament, we focused on collecting the Twitter follower data for the entire month only.

his notch is downward, which means that the more he played the tournament the less he gained the followers. For third player id "Poonage" we see that his Twitter following does not have any effect on the tournament he plays.

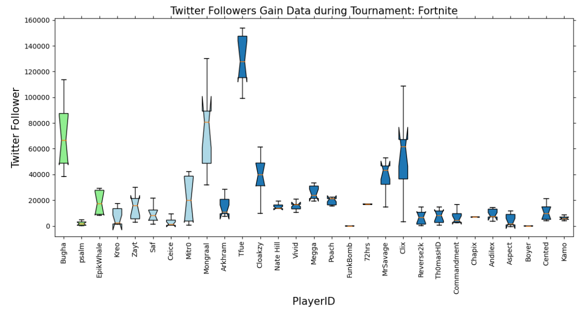

Figure 7: Twitter Follower Gain Data during Tournament for Fortnite

The Figure 7 shown for Game "Fortnite" which tells the behaviour for 30 players during a Tournament. Here, we find that 19 players lost their followers, 9 players gained followers while 2 player didn't have any effect on Twitter follower data.

For e.g. ninth player id "Mongraal" notch is pointing upwards, which means that the more he plays the tournament, the more he gained Twitter followers while it is opposite for tenth player id "Arkhram", his notch is downward, which means that the more he played the tournament the less followers he gained. For second last player id "Cented" we see that his twitter follower didn't have any effect on the tournament which he played.

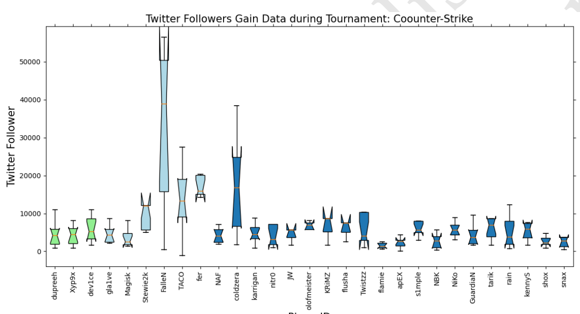

Figure 8: Twitter Follower Gain Data during Tournament for Fortnite

The Figure 8 is shown for the game "Counter-Strike" which tells the behaviour for 30 players during Tournament. Here, we found that 13 players lost their followers, 17 players gained followers.

For e.g. fifth player id "dupreeh" notch is pointing upwards, which means that the more he played the tournament, the more he gained Twitter followers while it is opposite for third player id "dev1ce", his notch is downward, which means that the more he played the tournament, the less followers he gained. In this case we have not found any player whose twitter follower have any effect on the tournament in out of top 30 players data sets.

2. Transfer details:- When a player is active and he transfers from one team to another team we then try to find some relation in **Twitter followers gain data during the transfer period** [3].

For e.g. a player named "Alin Raj" with an id "Vampire" transferred from team "Orange Rock" to "Element Esports" on "2020-05-14" and from team "Element Esports" to "GodLike Esports" on "2020-06-17". Therefore, the Twitter followers gain data for the entire month of May 2020 and June 2020 stored and used for analysis.

The above process repeated for his each transfer and we collected the Twitter followers gain data for that month in order to find some relation between them.

For all players, we collected these data and later we plotted them with the help of a box and whiskers plot. We applied the notches in the box plot to obtain the popularity of that player based on Twitter followers data that a number of the transfers has really some impacting on Twitter followers gain count or not.

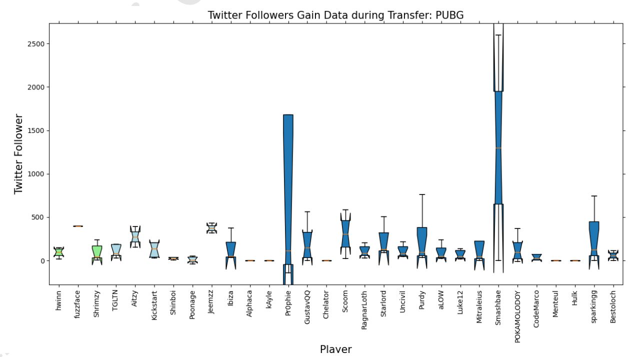

Figure 9: Twitter Follower Gain Data during transfer for PUBG

The Figure 9 shown for Game "PUBG" which tells for 30 players data-sets behaviour during transfer from one team to another. Here, We found that 17 players loses their followers, 3 players gain followers while 10 player does not had any effect on twitter followers data.

For e.g. sixth player id "kickstart" notch is pointing towards upwards means that the more he transfers from one team to another the more he gain Twitter followers. Mean in his each transfer the follower count is more compared to previous transfer. While it is opposite for third player id "shrimzy", his notch is downward side which means that the more he transfers the the less he gets twitter followers. For first player id "hwinn" it is seen that his twitter follower does not have any effect on the tournament which he plays because sometimes he is getting more followers some it's opposite and overall it is seen that using median that it passing the from exactly second Quartile.

[3]Twitter followers gain data during the transfer period: Generally, when a player transfers from one team to another, he informs a few days early and in this process, many of his followers take some decision to either keep following him or not. Similarly, the team in which he is transferred to, advertise this information, spreading the news that a new player will be going to join their team, which again made the followers of this team take some decision either to follow the new player or not.

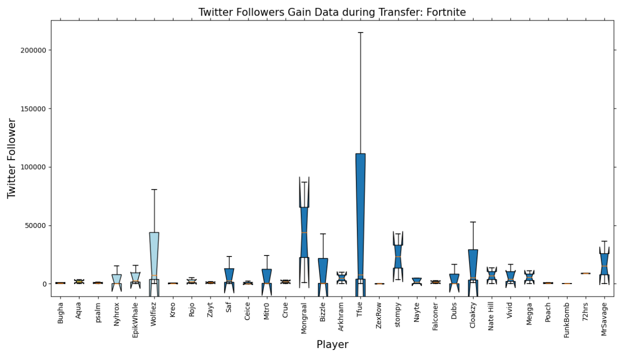

Figure 10: Twitter Follower Gain Data during transfer for Fortnite

The Figure 10 shown for Game "Fortnite" which tells for 30 players data-sets behaviour during transfer from one team to another. Here, We found that 15 players loses their followers, 14 player does not had any effect on twitter followers data and for this case and only 1 player in top player 30 does not have any impact on twitter follower in his transfer from one team to another.

For e.g. fourth player id "Nyhrox" notch is pointing towards downwards which means the more he transfers from one team to another the more he loses Twitter followers. For second player id "Aqua" it is seen that his twitter follower does not have any effect on the tournament which he plays because his notch is pointing in both upwards as well as downwards direction also his is exactly same as his second Quartile.

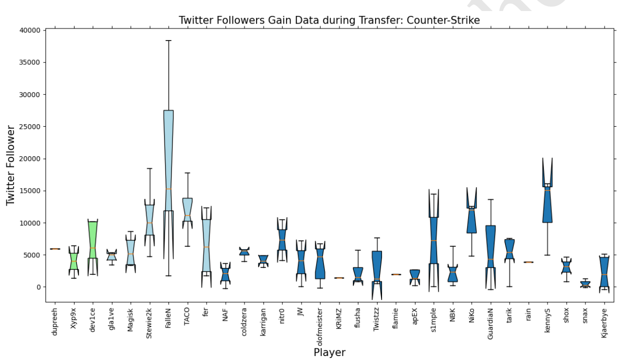

Figure 11: Twitter Follower Gain Data during transfer for Counter-Strike

The Figure 11 shown for Game "Counter-Strike" which tells for 30 players data-sets behaviour during transfer from one team to another. Here, We found that 14 players loses their followers, 10 players gain followers while 6 player does not had any effect on twitter followers data.

For e.g. eleventh player id "coldzera" notch is pointing towards upwards means that the more he transfers from one team to another the more he gain Twitter followers. Mean in his each transfer the follower count is more compared to previous transfer. While it is opposite for third player id "dev1ce", his notch is downward side which means that the more he transfers the the less he gets twitter followers. For second player id "Xyp9x" it is seen that his twitter follower does not have any effect on the tournament which he plays because his notch is pointing in both upwards as well as downwards direction also his is exactly same as his second Quartile.

3 RESULTS

3.1 Pearson Correlation Coefficient Results

After collecting data for all players, we find the average of the correlation as well as the mean of the data, for both the positive and the negative values and see the following results:

Total number of Positive R	265
Total number of negative R	326
Percentage of Positive R value	44.83925549915397
Percentage of Negative R value	55.16074450084603
Mean of Positive R value	0.4580981132075472
Mean of Negative R value	-0.5674202453987734

Table 1: Counter Strike Achievement Data

Total number of Positive R	199
Total number of negative R	324
Percentage of Positive R value	38.04971319311664
Percentage of Negative R value	61.95028680688337
Mean of Positive R value	0.6488994974874374
Mean of Negative R value	-0.6471697530864199

Table 2: Counter Strike Transfer Data

For Counter-Strike, the achievements data has a positive "r" of 44.8% and for transfer data, a positive "r" of 38%. This shows that overall, the players who participated in a tournament, gained more followers for that event, compared to when they were involved in a transfer. But if we look at the overall data, we see that the Percentage of the negative correlation is much higher in both cases, specially in Transfers. Therefore, a definite conclusion we gather is that overall, the players loose followers in both the cases, whether they participate in a tournament or transfer to another team.

Total number of Positive R	60
Total number of negative R	44
Percentage of Positive R value	57.692307692307686
Percentage of Negative R value	42.30769230769231
Mean of Positive R value	0.5524666666666668
Mean of Negative R value	-0.5919318181818183

Table 3: Fortnite Achievement Data

Total number of Positive R	14
Total number of negative R	10
Percentage of Positive R value	58.333333333333336
Percentage of Negative R value	41.66666666666667
Mean of Positive R value	0.9157142857142857
Mean of Negative R value	-0.915

Table 4: Fortnite Transfer Data

For Fortnite, the achievements data has a positive "r" of 57.6% and for transfer data, a positive "r" of 58.3%. This shows a different outcome, as the players who participated in a tournament, gained less followers for that event, compared to when they were involved in a transfer. But if we look at the overall data, we see that the Percentage of the positive correlation is much higher in both cases, especially in Transfers. Therefore, a definite conclusion we gather here is that overall, the players gain followers in both the cases, whether they participate in a tournament or transfer to another team, with it affecting more during a Transfer than during a tournament.

Total number of Positive R	30
Total number of negative R	70
Percentage of Positive R value	29.126213592233007
Percentage of Negative R value	70.87378640776699
Mean of Positive R value	0.38870000000000005
Mean of Negative R value	-0.4987397260273972

Table 5: PUBG Achievement Data

Total number of Positive R	24
Total number of negative R	43
Percentage of Positive R value	35.82089552238806
Percentage of Negative R value	64.17910447761194
Mean of Positive R value	0.6863333333333332
Mean of Negative R value	-0.7331860465116279

Table 6: PUBG Transfer Data

For PUBG, the achievements data has a positive "r" of 29.1% and for transfer data, a positive "r" of 35.8%. This shows a similar outcome as Fortnite when comparing just the Gain, as the players who participated in a tournament, gained less followers for that event, compared to when they were involved in a transfer. But if we look at the overall data, it is much more like Counter-Strike, as we see that the Percentage of the Negative correlation is much higher in both cases, especially in Achievements.

Therefore, a definite conclusion we gather here is that overall, the players lost followers in both the cases, whether they participate in a tournament or transfer to another team, with it affecting more during an Achievement than during a Transfer.

3.2 The Box and Whiskers Plot Results

We scraped the 1000 players' data for each game and we found that 632, 108, and 109 players' data for the respective game Counter-Strike, Fortnite, and PUBG have both Twitter followers and achievement data as shown in the table 7. Since, for the Counter-Strike, few players do not have the information regarding the achievement on Liquipedia therefore, only 632 players data we managed to scrap for our analysis. It is seen that for Fortnite and PUBG game, only few players have the Twitter account and so only available data is used for the analysis.

For the Counter-Strike game, we found that out of 632 players 213 players gained, 333 players lost while for 86 players, Twitter follower gain data does not have any impact overall as seen from the Box and Whiskers Plot [4]. We also saw that the more the player playing the tournament, the more the number of Twitter followers gain data is decreasing. As per the shown table which says that for 52% it's loss, 33% it's gain and only 13% it is uniform.

For the Fortnite game, we found that out of 108 players 34 players gained followers, 59 players lost followers while 15 players' Twitter follower gain data did not have any impact overall as seen from the Box and Whiskers Plot. As per the shown table 7 which says that for 54% it's loss, 31% it's gain, and only 13% it is uniform gain.

For the PUBG game, we found that out of 109 players 38 players gained followers, 69 players lost followers while only 2 players' Twitter follower gain data does not have any impact overall as seen from the Box and Whiskers Plot. As per the shown table 7 which says that for 63% it's loss, 35% it's gain, and only 2% it is uniform gain.

Therefore, overall it is seen that for all three games, the loss in Twitter followers gain data is observed, which also says that the more a player plays tournament the more is the chance that the number of followers gains concerning the previous tournament will be less in comparison to the current tournament for each game Counter-Strike, Fortnite and PubG. For PUBG it is very little chance that we would not see any effect on tournament playing because of only 2% uniformity seen from the plot. For all these games there is more than one-third chance that they may gain in followers count while playing the tournament compared to the previous tournament.

Follower	Counter Strike (632)	Fortnite (108)	PubG (109)
Gain	213 (33%)	34 (31%)	38 (35%)
Loss	333 (52%)	59 (54%)	69 (63%)
Uniform	86 (13%)	15 (13%)	2 (2%)

Table 7: Twitter Followers Gain Data during Tournament for 1000 players for game Counter-Strike, Fortnite and PUBG

We also scraped the 1000 players data for each game to observe the transfer from one team to another and we found that 723, 277,

[4]Box and Whisker Plot observation: The median of box plot can be more, equal or less than the second Quartile for the player data sets which says that respective player gain, loss or uniform in Twitter followers gain data. The Twitter follower count may be positive or negative. The notches shown in the box plot say where this data is flowing. Also, if the notches are in both the directions then for that player the data is not clearly saying that it is increasing or decreasing but we kept our result only basis on the median.

and 205 players data for the respective game Counter-Strike, Fortnite, and PUBG have both Twitter followers and transfers details as shown in the table 8. Since, for Counter-Strike game, few players do not have the information regarding the transfers on Liquipedia therefore, only 723 players data we managed to scrap for our analysis. It is seen that most of the Fornite and PUBG players are belonging from the either China or South Korea where Twitter has been banned so very little Twitter account holder who plays these games have the Twitter account, therefore, only available data is used for the analysis.

For the Counter-Strike game, we found that out of 723 players 161 players got to gain, 381 players got loss while 181 players' Twitter follower gain data does not have any impact overall as seen from the Box and Whiskers Plot. We also saw that the more the players transfer from one team to another the more in the number of Twitter followers gain data decreasing is seen. As per the shown table which says that for 52% it's loss, 22% it's gain and 25% it is uniform.

For the Fortnite game, we found that out of 277 players 16 players got to gain, 83 players got loss while 178 players' Twitter follower gain data does not have any impact overall as seen from the Box and Whiskers Plot. As per the shown table 8 which says that for 30% it's loss, 5% it's gain and a significant amount 65% of players Twitter followers gain data is uniform.

For the PUBG game, we found that out of 205 players 36 players got to gain, 90 players got loss while only 79 players' Twitter follower gain data does not have any impact overall as seen from the Box and Whiskers Plot. As per the shown table 8 which says that for 44% it's loss, 18% it's gain and 38% it is uniform gain.

Therefore, overall it is seen for all three games that the loss in Twitter followers gain data is observed, which also says that the more a player transfer from one team to another the more is the chance that the number of follower gain with respect to the previous transfer will be less in comparison to the current transfer for each game Counter-Strike, Fortnite and PubG. For PUBG, we saw that a significant amount of players' data is not impacting the team transfer. For all these games there is more chance that they may lose in followers count while transfer from one team to another.

Follower	Counter Strike (723)	Fortnite (277)	PubG (205)
Gain	161 (22%)	16 (5%)	36 (18%)
Loss	381 (52%)	83 (30%)	90 (44%)
Uniform	181 (25%)	178 (65%)	79 (38%)

Table 8: Twitter Followers Gain Data during Transfer for 1000 players for game Counter-Strike, Fortnite and PUBG

4 DISCUSSION

4.1 Pearson Correlation Analysis

- Out of the three games, we see that for two of three games (Fortnite and PUBG), the transfers of a player positively affected his follower gain compared to when he participated in a tournament during his Active years.
- Overall, followers are not heavily dependent on both Achievements or Transfers as the Negative Value is always higher for all three games.
- , Therefore, there are many more variables that can help us find better relation between followers, rather than the Achievements or Transfers.
- Lack of data creates outliers in the overall data set, which leads to an effect in the "r" value, and therefore, with more data, we can have a much more conclusive answer.

sub Analysis and Evaluation Method 2:

5 SUMMARY AND CONCLUSION

Through our analysis of the three games PUBG, Fortnite, and counterstrike, it's been proven that the active years and transfers do affect the overall popularity (Twitter followers) of the player, but negatively. As you can see through our analysis, that achievements and transfers had a negative impact on the follower count, which means players lost followers generally. But that begs the question, why is there a negative impact in general for twitter popularity? It might be that the overall popularity of the game itself might be a reason why players lost followers as there are fewer people who follow the games. Or it might be that followers might be more loyal to teams rather than the player themselves because of which they don't follow the player individually, one more explanation might be Players who take retirement from Playing Professionally lose followers and therefore, impact the overall correlation. More factors such as Age, Team, Region, and Tier might affect the overall followers as well.

6 CONTRIBUTIONS

(1) Ajay Kesarwani
- Scrapped the Achievement details for each players for each games.
- Written and analysed the relation between the follower with achievement for each player by adding box and whiskers plot.
- Written and analysed the relation between the follower with transfers for each player by adding box and whiskers plot.

(2) Aditya Jain
- General code structure for scrapping data from Liquipedia using Beautiful Soup.
- Code for Correlation Analysis using Pearson Correlation Coefficient for Achievement Data and Twitter followers
- Code for Correlation Analysis using Pearson Correlation Coefficient for Transfer Data and Twitter followers
- Deriving conclusion for Pearson Methodology and finding results for the same.

(3) Mustafa AlShaidat
- Code for scrapping data from twitter using Beautiful Soup and Selenium
- Code for Correlation Analysis using Pearson Correlation Coefficient for Achievement Data and Twitter followers.
- Final report structure and improvements.

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