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COSC300 Visualisation Report

Semester 1 - 2020

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1 Introduction

Super Smash Bros. Ultimate, a game for the Nintendo Switch is an immensely popular game with an amazing competitive community nationwide. This report was created with the aims of giving the Australian competitive community a better insight into character changes and skill gaps between each quarter of 2019 and differences between rising skill levels of states. This insight will be properly visualised through multiple data graphs including that of univariate, bivariate and multivariate representations.

2 The Data Set & Problem Statement

Hello and welcome to my report about data visualisation. My name is Natalie and I am a third year Software Engineering student and I'm enjoying this course so far.

2.1 The Data Set

The data set I have chosen is that of character usage, skill gain and played matches revolving around that of a local competitive gaming community in Australia. The way I have chosen to present this data set is through that of local JavaScript which calls the Google Chart library. This means that I will be able to deploy a live website showing this data for later viewing and later analysis.

2.2 Problem Statement

As data is always changing in database I was using, I decided to only pull data from last year (2019) to give a more accurate representation of data and split them into each quarter (every 3 months).

I also chose to choose this data set as I believe that no clear visualisation of character data usage, elo gain and state comparison currently exists within the community and presenting this data in will allow for a more insightful look into the past and how the metagame (accepted norm) of the community has changed.

I also wanted to find answers to these questions using my visualisations:

- Does the amount of players influence the elo gain?
- Do more players mean better results?
- What is the relation between top played characters and elo gain?
- How did character usage change between each quarter?
- Which state performed the best in which quarter?
- Which quarter had the best performance?

I hope that you will find this interesting even if you don't play games.

3 Techniques, Methods and Execution

In this section, I will talk about my approach to the data collection; how I handled the data and how I displayed the data in web form.

3.1 Techniques - The Approach to the Data

The data that I was trying to access was that of a public API that I could easily access through Python.

The data was stored in JSON form which meant that I had to iterate through various levels of data to get the data that I wanted.

Since I was on a mac, I had to create a virtual environment to be able to access the API. Once I set up this environment, I created a Python script then called the API using a variety of similar functions to the code block below.

```
headers = {'Content-Type': 'application/json',
           'X-APIKey': '6PG30WV9UCVFZNTXQJKR'}

# ID being the character ID
def character_matches(id):
    url = 'https://api.ausmash.com.au/characters/{}/matches'.format(id)
    response = requests.get(url, headers=headers)

    content = json.loads(response.content)
    # JSON file of the content received and returned. It can now be stored for further
    # use.
    return content
```

Using similar functions to the above, I was able to create a large dictionary in Python which contained all my data. This structure was split into quarters, by state and then by characters, with each character containing the unique players, the amount of elo gained and the amount of matches played. How I was able to sort this data into a more readable and interactable form can be seen in the next section.

[\(Click for API Documentation\)](#)

3.2 Methods - How I Handled the Data

Before working towards getting my data, I had decided that I wanted to pull elo gain (skill gain, it will be called elo throughout the report), the unique amount of players who played each character and the amount of matches played for the specific character. Each character's data would then be sorted into states which would then further be stored into quarters (every 3 months e.g. Q1 is from January 1st 2019 to March 31st 2019).

To do this, I iterated through every single character's logged matches and got each unique player, their state and the won elo if the player won the match. I would also get the date and would match the date to the associated quarter. Once this was done, I then added their data to a large dictionary data structure.

Once the data was fully sorted, I wrote the contents of the dictionary into a JSON file which was then to be used for my JavaScript file which would display the data using Google Charts. This JavaScript usage will be explained in the next section.

3.3 Execution - Displaying the Data

Using [Google Charts](#) I was able to create various suitable graphs for my collected data using native JavaScript. The chosen graphs that were used for my data visualisation were that of:

- Bar Charts
- Bubble Charts
- Line/Area Charts
- Scatter Plots (using the same library as Bubble Charts)
- Step Graphs

Order of iteration through my chosen data would change depending on which graph I had chosen and what I wanted to display. This led to many different variances of the same code which would each have different outcomes. For example, for some code I would need to iterate through quarters rather than the states. When running the script for my data, I also made sure to check the player's state of origin rather than where they competed to account for interstate tournaments and visits.

When I wanted to create the specified chart, I would create an array to hold the data in it called 'overallData'. This array would then hold more arrays which would correspond to different datapoints and axis that I wanted to display depending on the chart that I had chosen.

A demonstration of the JavaScript code used to display the chart can be seen below.

```
function drawChart() {
  var data = google.visualization.arrayToDataTable(
    overallData
  );

  var options = {
    title: chartTitle,
    width: 1800,
    height: 800,
    vAxis: {
      title: 'Y axis name'
    },
    hAxis: {
      title: 'X axis name'
    }
  };

  var chart = new
    google.visualization.ChartType(document.getElementById("chart-div"));
  chart.draw(view, options);
}
```

Using similar code blocks to this, I was able to create the following graphs which will be analysed in the next section.

Note: For a more detailed look into my code check out the supplied code.

4 Data Analysis

Before beginning my data analysis, I decided to group my data into little subsections. These being:

- Player and Match Data
- Character Data
- Elo Data
- Combined Data

4.1 Player and Match Data Analysis

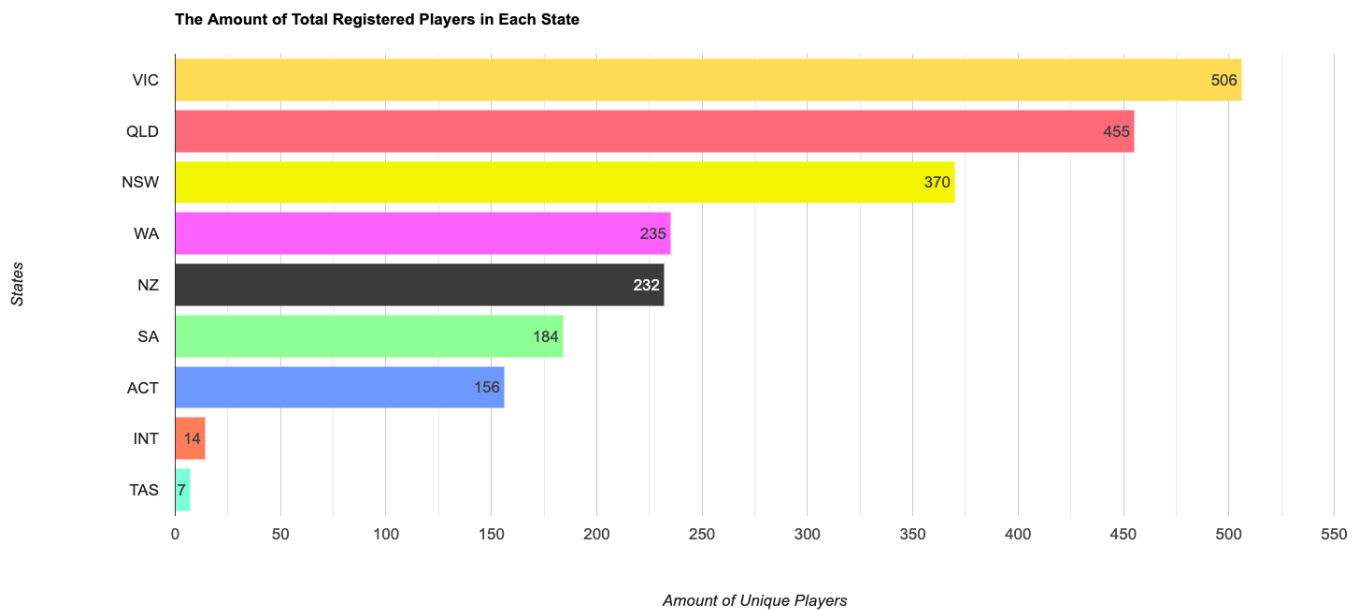


Figure 1: The Total Amount of Registered Players in Each State (2019)

The first graph that I wanted to display was that of unique players that had played in each state. From this graph, it is possible to see that Victoria (VIC) had the most registered players in 2019 while Tasmania (TAS) and International (INT) players have the smallest registered players, this may be due to the populus size of TAS and the lack of international competitors entering Australian tournaments.

It's worth noting that New South Wales (NSW) should have a much larger registered playerbase due to its large population compared to all the other states. This however, does not seem to be the case, making it an outlier in the dataset. This could be due to a lack of tournaments held per week which can lead to a struggle in encouraging new players to join the gaming scene. If you would like a further look into the exact values for the following graphs, please check out [stepGraph.html](#) and [barGraphs.html](#) supplied in the Visualisation Project folder.

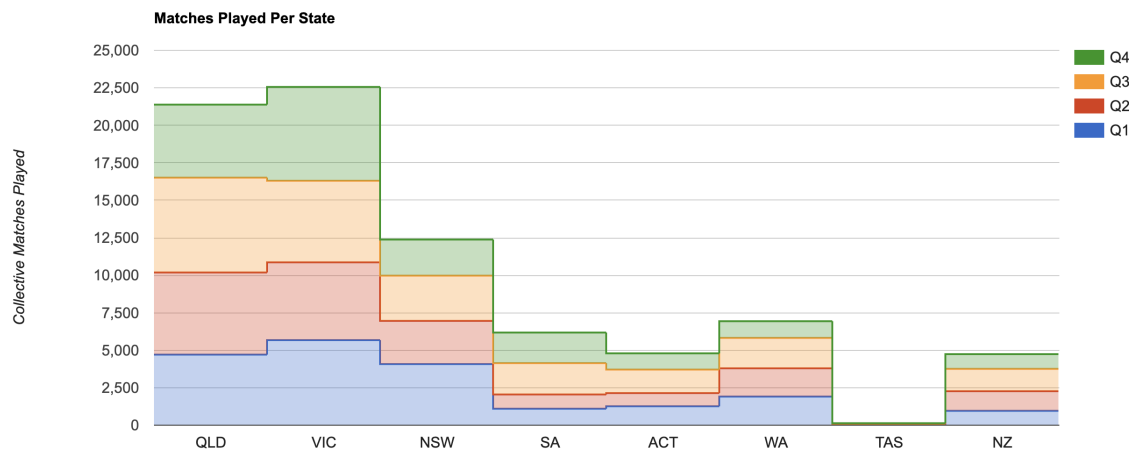


Figure 2: Step Graph Representing The Amount of Matches Played in Each State (2019)

Figure 2 shows the amount of matches that were played each quarter (Q) for each state. From the analysis of Figure 1, it is clear that the amount of players in a state can impact the total amount of matches played each quarter. As per Figure 1, VIC remains the state with the most amount of matches played across the year due to their large registered playerbase.

Something not seen within Figure 1 that is seen in that of Figure 2 is that in the first quarter, NSW and QLD had a similar amount of matches played. This may have been due to the game's recent release as it came out in December which would've have brought many new players to start the year off with but as time went on, NSW players started to drop out of the scene and stop playing which resulted in less matches played in NSW for the rest of the year as the quarters following Q1 resulted in less matches played. One reason for NSW to have such a drop off in player base may be due to its community not being able to engage with new players properly unlike that of VIC and QLD's older communities which have been around since early 2010's, allowing them to be more experienced with new players.

It is also noticeable that TAS has almost no matches played in every quarter, each being around 27 for most of them which was also evident in Figure 1.

Since matches played isn't too much of a good measure of constant activity within a community. I decided to divide the total amount of matches by the players within each quarter to see if any further trends could be found.

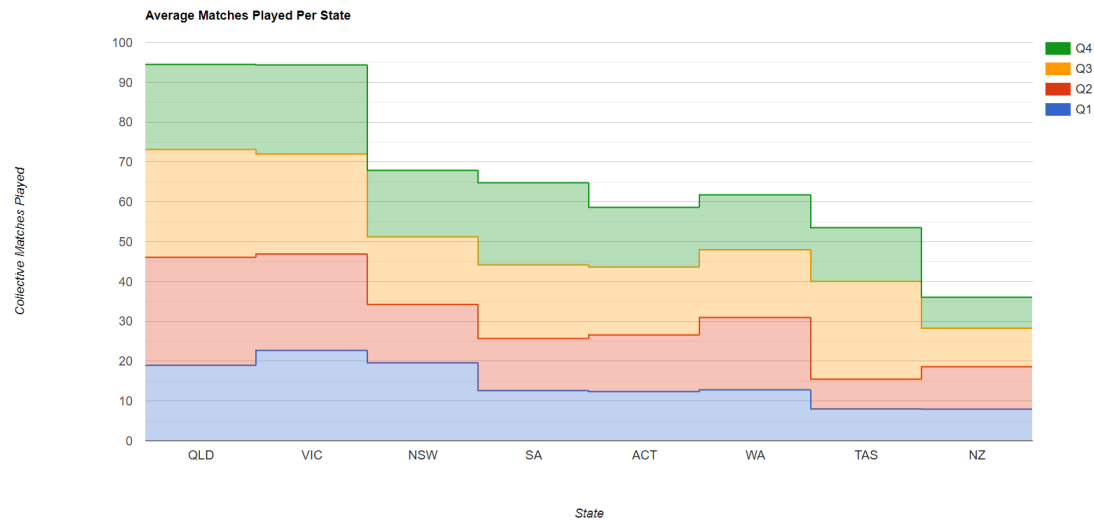


Figure 3: Step Graph Representing The Average Amount of Matches Played in Each State (2019)

This graph differs very differently from the previous one. One noticeable difference being that of Tasmania's matches played. In the previous figure, TAS was barely visible in comparison to other states, with the average calculation in play. It is possible to see that the TAS' competitive scene is rather active as each individual player is active. Similar to the other graph, New Zealand (NZ) has very steady data, with the amount of matches played and that of active players. From this, it is possible to assume that NZ players all have very similar attendance. This may be due to the fact that NZ does not have weekly tournaments but rather monthly ones.

4.2 Character Data Analysis

When creating the bar graphs for this section of analysis. I decided to create an interactive bar graph which could show the character usage for each quarter per state and for the whole of Australia. Of course, this ended up with 32 different bar graphs to analyse... which I wasn't going to do. Instead, I will be analysing each quarter for the whole of Australia, there is a possibility that each graph will be looked at during the supplied presentation. It is also worth noting that due to the previous figures having a lack of non-average TAS and INT data, I have decided to take it out as they are outliers and are not good for individual analysis. If you want a further look into the interactivity and to look at all 32 bar graphs, please check out [barGraphs.html](#) supplied in the Visualisation Project folder.

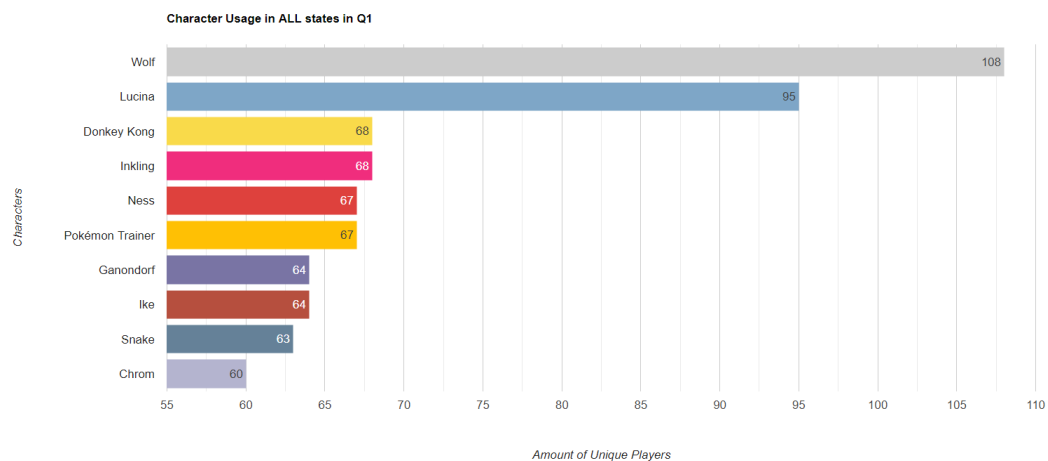


Figure 4: Character Usage in Australia, Q1 (2019)

Quarter 1 consisted of the time period spanning from the 1st of Jan to the 31st of March. During this time, no additional fighters were added to the game and it was relatively new. Due to the size of Smash Ultimate's character roster, many characters who did not appear in the previous game were added in game (Ultimate). This meant that fans who had missed older characters were finally able to play them again in this game. An example of this is Wolf, an older character who was not in the game before's roster. On the announcement of his return to the game, many fans were very eager to play him and explain his high usage within the first quarter. Similar to Wolf, Pokemon Trainer and Snake were also returning characters who were fan favourites which once again explain their popularity.

Other characters such as Lucina were popular in previous games meaning when transitioning between games, players would choose characters they were more familiar with which would explain their popularity.

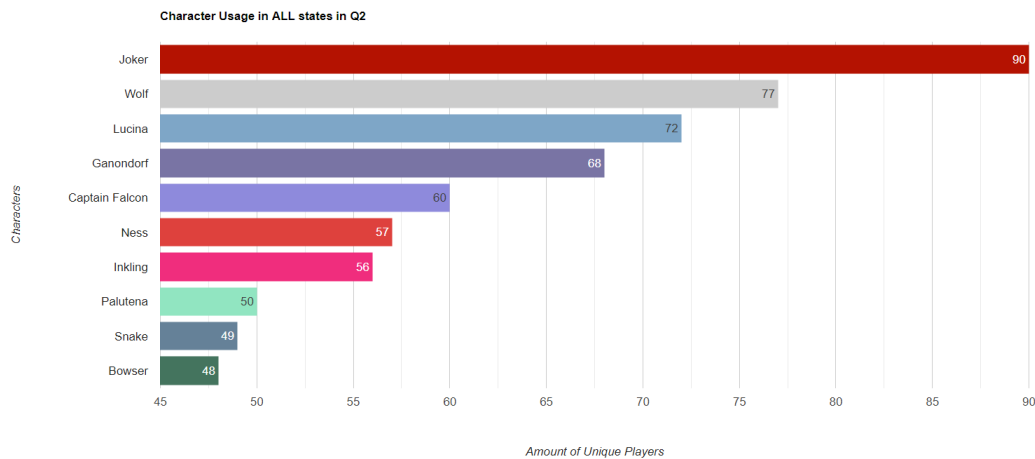


Figure 5: Character Usage in Australia, Q2 (2019)

Quarter 2 was when the first character (Joker) was added to the game. With the game still evolving and excitement revolving around the addition of the new character, players were eager to try out the new character. Although Joker was the most picked character for this quarter, there are less players who have chosen Joker than Wolf when comparing Q2 to Q1. This may be due to players dropping off

It is also worth noting that the two most played from Q1 (Wolf and Lucina) remain in the same order, meaning that players were more comfortable with them. Characters such as Palutena and Bowser have also appeared in this top 10 usage graph. This may be due to players branching out and experimenting with new characters.

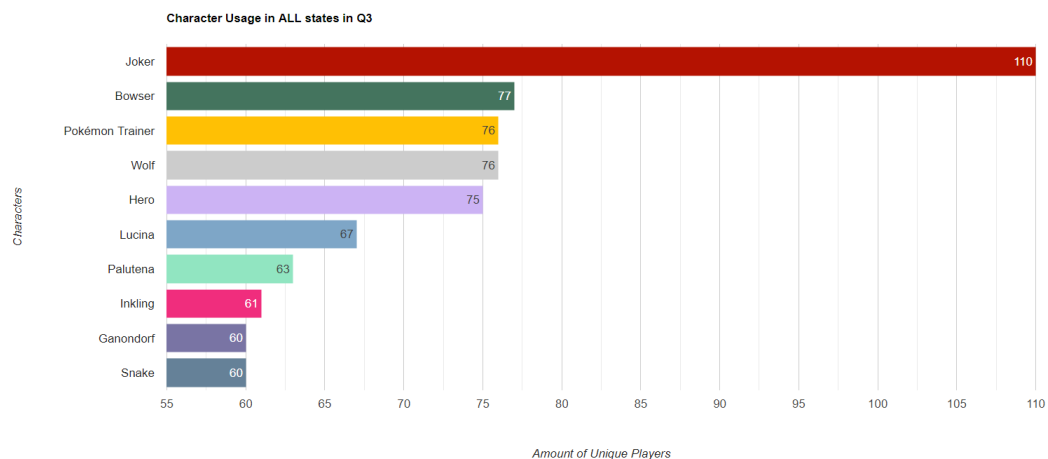


Figure 6: Character Usage in Australia, Q3 (2019)

Quarter 3 occurred from the 1st of July to the 30th of September. During this time, another character (Hero) were added to the roster. Of course, players were eager to play him but his popularity was not enough to put him in the most played spot like Joker. This lack of popularity may be due to his moveset being controversial and based upon luck, resulting in some states banning the character and therefore, not allowing the whole of Australia to play him.

In this quarter, it is interesting to see that Joker is played significantly more than any other character, even overtaking Wolf's usage in Q1 (Figure 4). This may be due to the metagame (the way the game is played) finally evolving and players realising that Joker is a good character

to play competitively. It is also worth noting that Bowser jumped from being the 10th most played in the country to the second most played within a quarter.

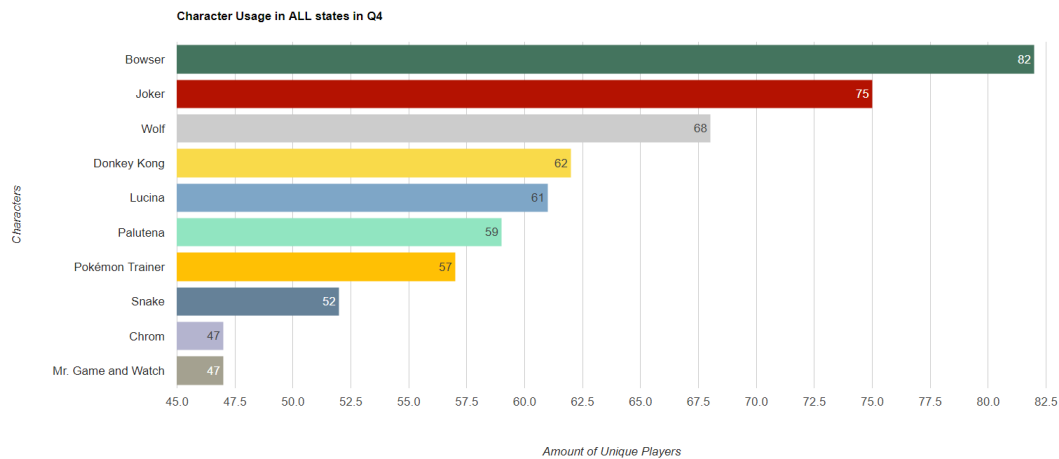


Figure 7: Character Usage in Australia, Q4 (2019)

Quarter 4 marks the end of the first year of competitive Smash Ultimate within Australia. Due to the previous two quarters, I expected this quarter to have Joker as the most played character but as you can see, he is not. Instead, Bowser is the most played. This may be due to players realising that Bowser's playstyle is more favoured for low level players which can allow them to win more games. Since there are a decent amount of low level players, it would make sense that Bowser would be played more than Joker in low level. This may be a reason that Bowser was picked more than Joker in this quarter.

Mr. Game and Watch has also appeared on this graph and hasn't been seen within any other quarters. This may be due to a top player [Maister](#) beating some of the best players in the world and inspiring Australians to pick him up.

4.3 Elo Analysis

Elo is that of skill rating within the smash community and acts as a way of seeing who is truly the best. When two players play a set against each other, they are to gain or lose elo based on an algorithm built into ausmash's backend. I however chose to look into purely elo gain as graphs could be more interesting as more elo is usually gained than lost within each state. If you would like to look further into the graphs in this section, please check out [lineGraphs.html](#) supplied within the Visualisation Project folder.

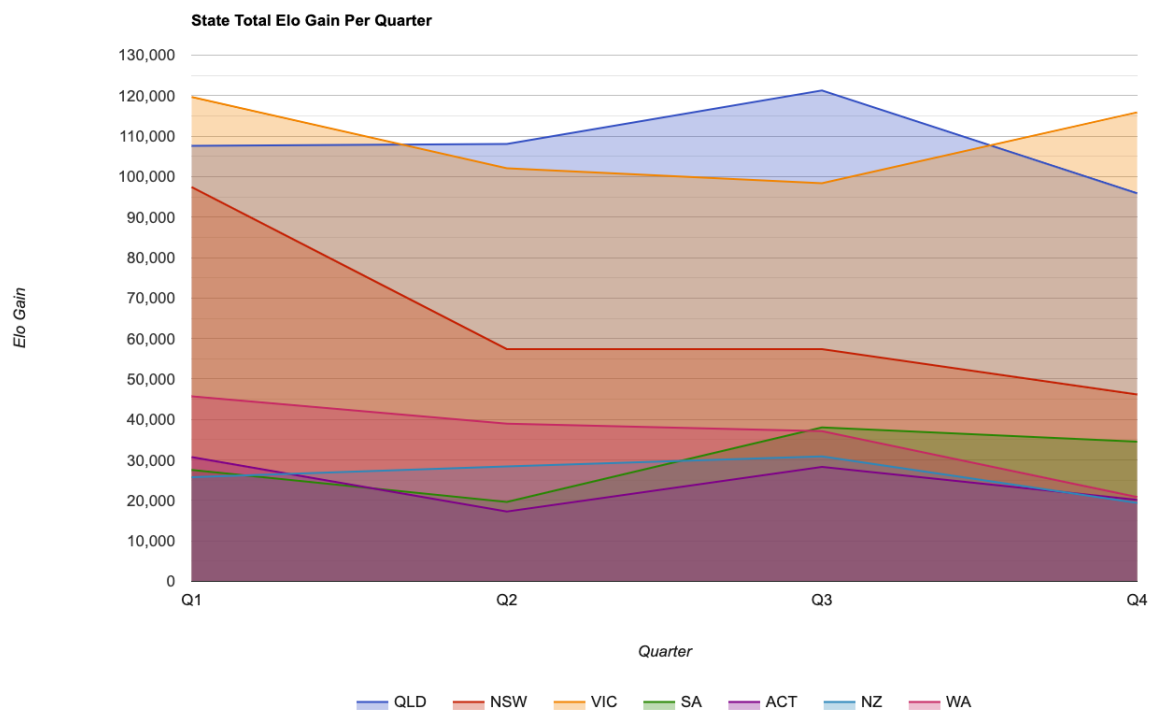


Figure 8: Line Graph Representing Total Elo Gain within each State (2019)

The above line area graph shows that of the fluctuating elo gain over each quarter of 2019. As seen in all previous graphs, QLD and VIC are always competing for the most elo/matches played due to their larger playerbases compared to other states. It's worth noting that VIC currently has the most top players residing in it which could result in more elo gain for players due to larger losses. Similar to what was seen in Figure 2, NSW has a large decline from Q1 to Q2 due to the player base greatly decreasing which results in less elo being gained. It's also notable that Q3 (July - September) has the largest difference between VIC and QLD. This was due to a lack of large events (majors) happening during this quarter. Only two majors were present during this quarter with one being in WA and the other being in QLD. This meant there were more opportunities for QLD players to gain elo as the tournament was local.

Since elo gain is similar to that of player size, I decided to divide to total elo gain by the amount of unique players each quarter to get an average elo gain within each state.

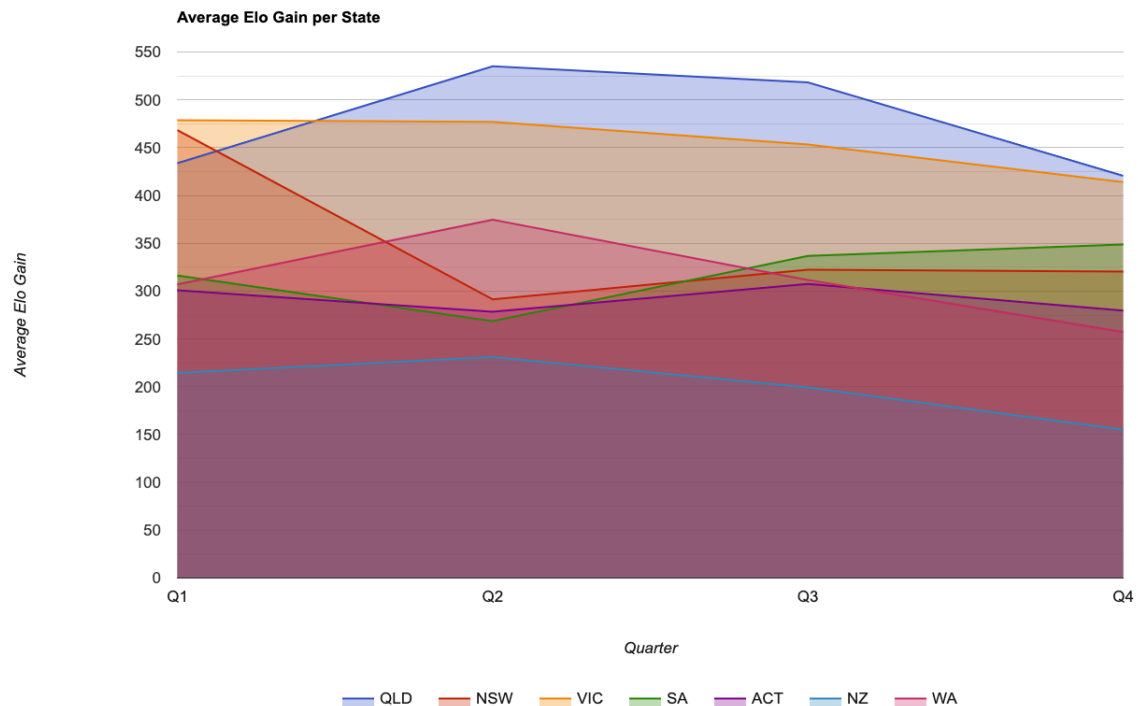


Figure 9: Line Graph Representing Average Elo Gain within each State (2019)

This change in from total to average elo gain can be drastically be seen. A main difference is that of the QLD vs VIC comparison and that of WA's spike in Q2. WA's spike particularly has not been seen in other graphs due to the player base size but due to the average calculation, it is easier to see the spike in Q2 where WA overtakes NSW in average elo gain. This could have been due to new characters being added to the game (Joker specifically) which could have allowed for players to perform better in tournaments.

From this figure alone, it is safe to assume that QLD had better players all around when compared to all other states in 2019. Although QLD was behind on average elo gain in Q1, as the game evolved, QLD was able to catchup and eventually have a better average elo gain.

As this was hard to analyse due to the line graph's colouring, I decided to use the same data points for a bar graph which can be seen in the figure below

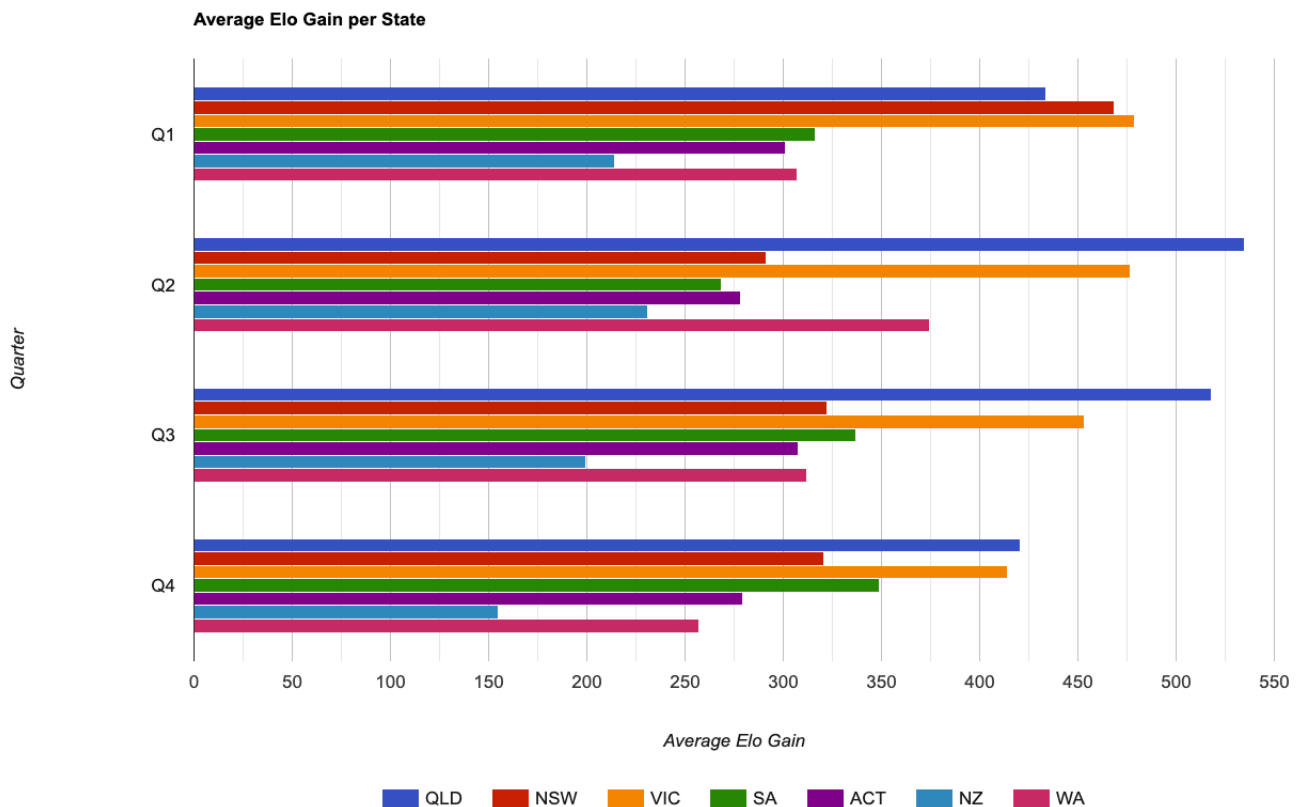


Figure 10: Bar Graph Representing Average Elo Gain within each State (2019)

What can mainly be seen within this bar graph is similar to that of the previous line graph but with states being easier to see. As stated before, WA had a large spike in average elo gain in Q2. This can be seen more clearly in the bottom bar of each quarter as WA slowly increases and spikes in Q2 before slowly going down for Q3 and Q4. It's also easier to see that ACT had a very steady average elo gain with no fluctuations. This may have been due to the relatively small but active player base.

Once again, it is safe to assume that QLD has better players all around due to its average elo gain across 2019 being much higher than other states for the majority of the year.

4.4 Multivariate Analysis

Multivariate analysis of the data consists of combining more than three data points from previous sections and using it for further analysis. The two main sections that will be analysed will be:

- Player Performance
- Character Performance

The reason that I have chosen to analyse performance with multivariate data is due to the fact that I wanted to display data on more than three axis as I am able to get a good indicator of how different players and characters perform. If you want a further look into exact values in these graphs, please check out [bubbleGraph.html](#) and [scatterPlot.html](#) supplied in the Visualisation Project folder.

4.4.1 Player Performance

Player performance graphs used the axis of elo gain, the amount of registered players and later on, quarters and states. In later scatterplots, you will see the data becomes easier to read as I add labels and colours to them.

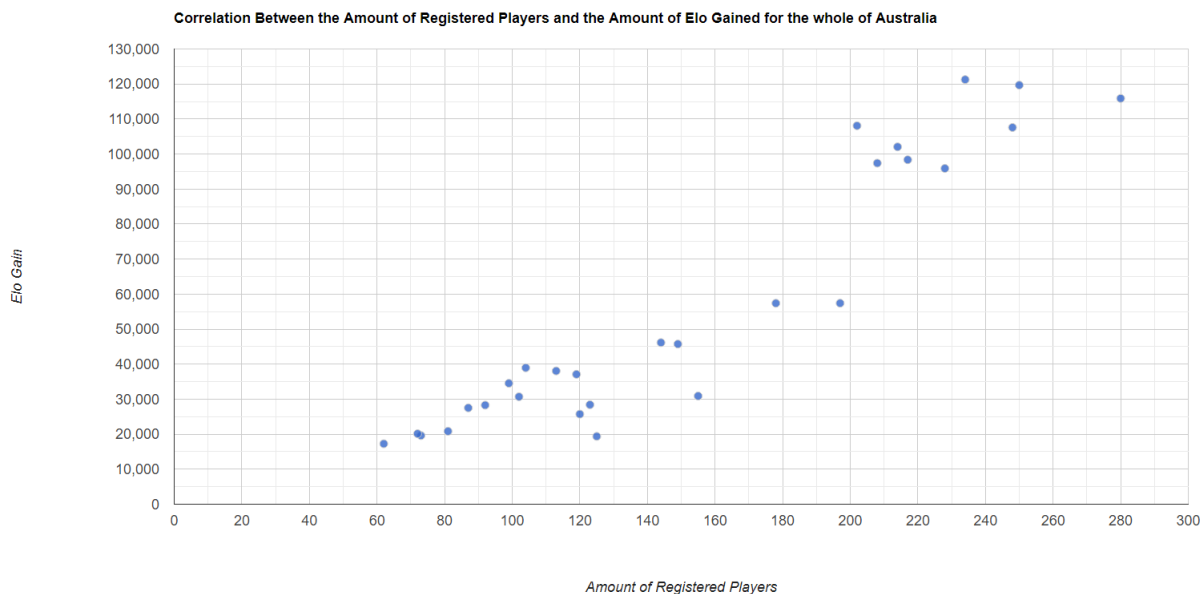


Figure 11: Player Performance in 2019

Figure 11 demonstrates a base graph with no colour. The point of this graph was to demonstrate and show the trend that the more registered players there are, the higher the elo gain for the players is. Each dot/point in this graph is representative of a state in a quarter which is looked at a little bit later but for now I wanted to show that this trend exists before adding more data points to it.

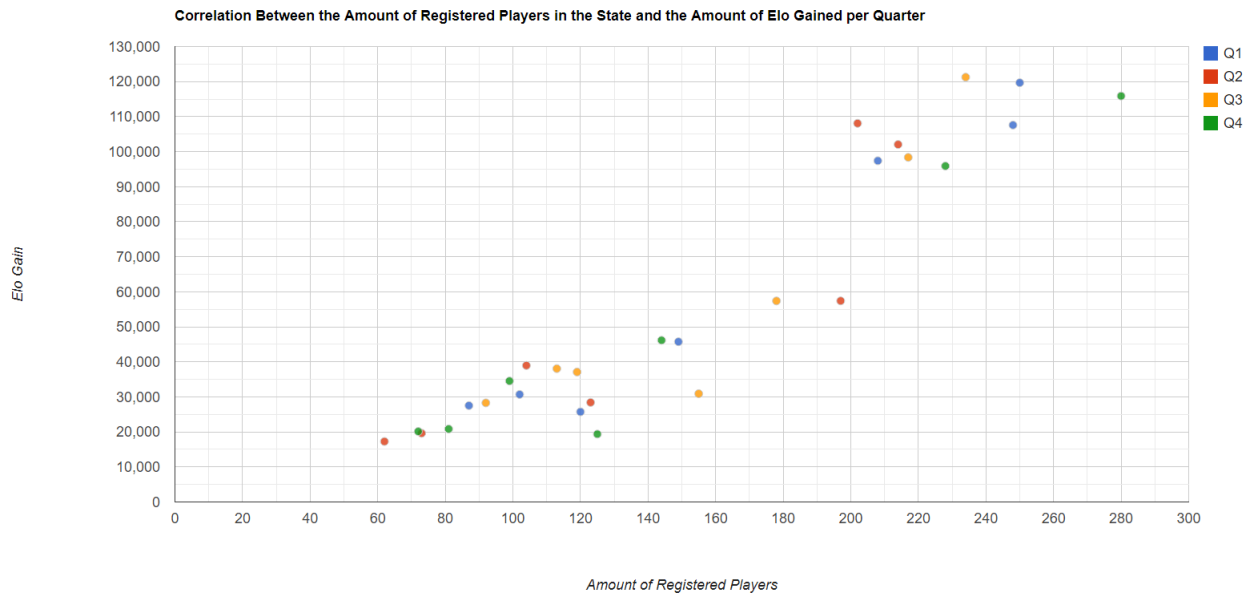


Figure 12: Quarters and Player Performance (2019)

Figure 12 shows the addition of quarters to the graph. What would be expected from this graph would be that of Q1 having the highest registered players and hence, the most elo gain. This is evident as the majority of the dots in the top right corner which represent the highest of both axis belong to that of Q1. It's interesting that the rest of the quarters have an even distribution in this top corner.

Q4 also had the most players for a state and is much larger when compared to other data points while Q2 for a state had the least amount of players recorded. For the first point, it is expected that this state would be a larger region (e.g. QLD or VIC) while the smaller point would be that of a smaller region (e.g. ACT, SA).

It's also worth noting that a state's performance in Q3 had the highest elo gain. This quarter was around the time of a QLD major so it would be expected that this dot is representative of QLD.

In the next figure, states were labelled in the scatterplot.

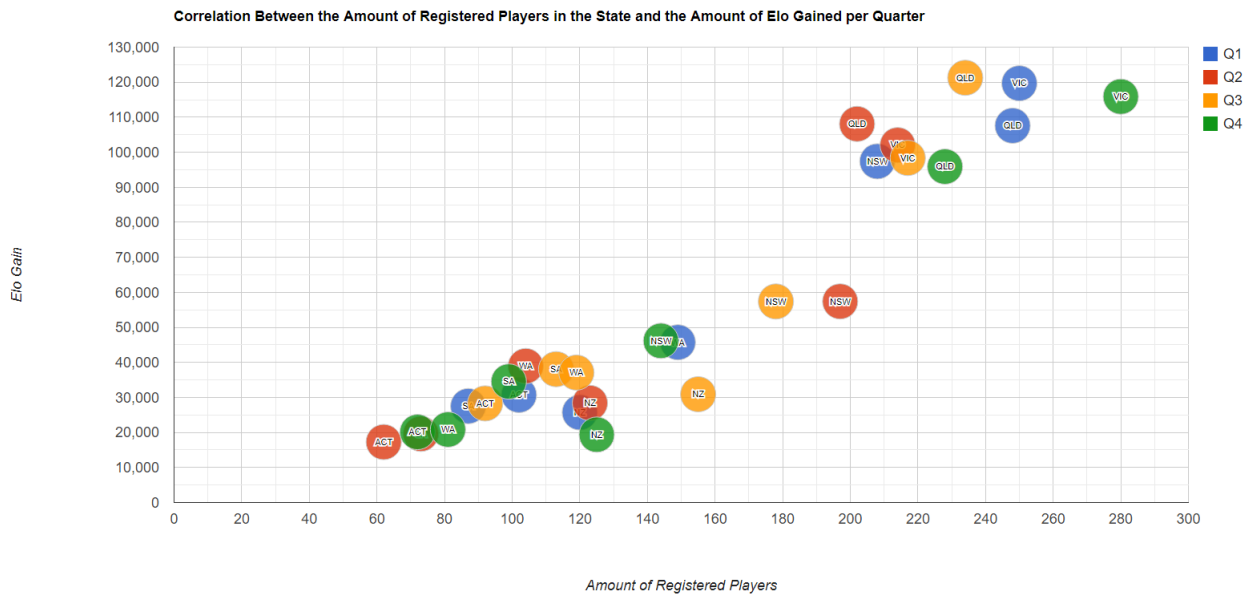


Figure 13: Quarters and Player Performance in States (2019)

In Figure 13, you can see the states added to the quarter labels. It's once again possible to assume that from the data that the more dominant states are that of VIC and QLD once again.

It was pointed out in the previous figure that a state in Q3 had the highest elo gain within the whole year and out of all the states. This lined up with my prediction of it being QLD due to the major event. This is also notable as this is the largest gap in elo gain between QLD and VIC but is still less than VIC and QLD's elo gain gap in Q4.

Since the majority of the bubbles in the top right (best performing section) were from Q1, it was safe to say that Q1 was the best quarter for performance.

As per previous figures, specifically in that of the elo gain analysis section. NSW can once again be seen significantly dropping off in elo gain after Q1.

One point that can be seen here that wasn't evident in previous figures is that of NZ in comparison to SA's Q4 performance. While the region had larger player base than SA, NZ underperformed and did not gain more elo than SA which stands as an outlier.

Another thing worth noting is that QLD in Q2 had better performing players than VIC. This can be seen as QLD in Q2 had more elo gain than VIC in Q2 despite having less players.

4.4.2 Character Performance

Character performance looks at quarters and 2019 as a whole. It aims to analyse and look into which characters were popular at the time and had the most elo gain. This would allow me to find the best performing characters within 2019. Similar to the previous section, each point in the graph represents a character and their usage within either the year or quarter. I once again start with plain versions of graphs to give a better overall analysis and then add more graphs and additional labels as figures progress. The main axis I had chosen for this section of analysis is that of matches played (x), elo gained (y) and player usage (radius). Please note that the Pokemon trainer got corrupted while creating this graph, I'm not sure why but please keep it in mind.

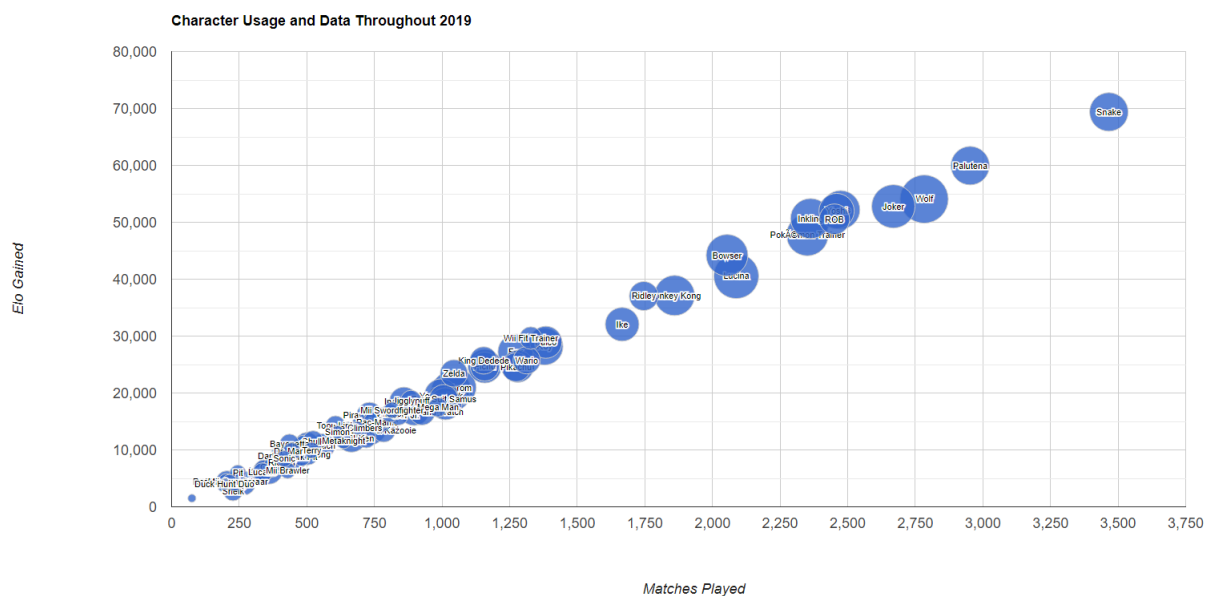


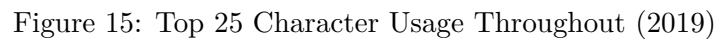
Figure 14: Character Usage Throughout (2019)

In this bubble chart, the best performing characters can be seen within the top right of the graph. The size of the bubble represents a characters unique player size. As seen within the character analysis section Wolf, Lucina, Joker and Bowser were the most popular within each quarter of 2019 and reflect this with their large radius. However, these characters are not the most popular/best performing ones as Snake and Palutena have a much higher elo gain and amount of matches played but have lower player counts. It's also clear that a trend exists between the amount of matches played and elo gained as the trend line for the data is linear. To take a further look into this data, I got the top 25 most played characters from this graph and added it to a heat graph to allow for a more in-depth look.

This graph demonstrates a selected top amount of characters with unique player usage being represented in colours which can be seen in the gradient legend above the graph.

What has changed within this graph is that of adding in colours in replacement of radius. There is an obvious hotspot near the top half of the graph where the most played characters are closer together which shows that they are performing well as they have entered many tournaments and gained a decent amount of elo. It was expected that the characters with the least players, matches and elo gained would reside in the bottom left so there are no outliers there.

With the addition of this colour gradient, it is now much more clear within this figure that ROB stands as an outlier. While other characters range more within midrange for usage within this



This scatter plot illustrates the relationship between the number of matches played and the Elo rating gained for various characters during each quarter of 2019. The x-axis represents 'Matches Played' (0 to 1,200), and the y-axis represents 'Elo Gained' (0 to 30,000). Characters are grouped by quarter: Q1 (blue), Q2 (red), Q3 (orange), and Q4 (green). The plot shows a general upward trend, with characters achieving higher Elo ratings as they play more matches. Notable outliers include Snake (Q1) and Joker (Q3), which achieved the highest Elo ratings in their respective quarters.

Character	Quarter	Matches Played (approx.)	Elo Gained (approx.)
Snake	Q1	1150	26500
Joker	Q3	1080	20500
Wolf	Q1	920	19500
Snake	Q1	780	18500
Palutena	Q1	700	17000
Snake	Q3	850	16500
Snake	Q3	880	15500
Snake	Q3	900	15000
Snake	Q3	920	14500
Snake	Q3	950	14000
Snake	Q3	980	13500
Snake	Q3	1000	13000
Snake	Q3	1020	12500
Snake	Q3	1040	12000
Snake	Q3	1060	11500
Snake	Q3	1080	11000
Snake	Q3	1100	10500
Snake	Q3	1120	10000
Snake	Q3	1140	9500
Snake	Q3	1160	9000
Snake	Q3	1180	8500
Snake	Q3	1200	8000
Snake	Q3	1220	7500
Snake	Q3	1240	7000
Snake	Q3	1260	6500
Snake	Q3	1280	6000
Snake	Q3	1300	5500
Snake	Q3	1320	5000
Snake	Q3	1340	4500
Snake	Q3	1360	4000
Snake	Q3	1380	3500
Snake	Q3	1400	3000
Snake	Q3	1420	2500
Snake	Q3	1440	2000
Snake	Q3	1460	1500
Snake	Q3	1480	1000
Snake	Q3	1500	500
Snake	Q3	1520	0
Snake	Q3	1540	-500
Snake	Q3	1560	-1000
Snake	Q3	1580	-1500
Snake	Q3	1600	-2000
Snake	Q3	1620	-2500
Snake	Q3	1640	-3000
Snake	Q3	1660	-3500
Snake	Q3	1680	-4000
Snake	Q3	1700	-4500
Snake	Q3	1720	-5000
Snake	Q3	1740	-5500
Snake	Q3	1760	-6000
Snake	Q3	1780	-6500
Snake	Q3	1800	-7000
Snake	Q3	1820	-7500
Snake	Q3	1840	-8000
Snake	Q3	1860	-8500
Snake	Q3	1880	-9000
Snake	Q3	1900	-9500
Snake	Q3	1920	-10000
Snake	Q3	1940	-10500
Snake	Q3	1960	-11000
Snake	Q3	1980	-11500
Snake	Q3	2000	-12000
Snake	Q3	2020	-12500
Snake	Q3	2040	-13000
Snake	Q3	2060	-13500
Snake	Q3	2080	-14000
Snake	Q3	2100	-14500
Snake	Q3	2120	-15000
Snake	Q3	2140	-15500
Snake	Q3	2160	-16000
Snake	Q3	2180	-16500
Snake	Q3	2200	-17000
Snake	Q3	2220	-17500
Snake	Q3	2240	-18000
Snake	Q3	2260	-18500
Snake	Q3	2280	-19000
Snake	Q3	2300	-19500
Snake	Q3	2320	-20000
Snake	Q3	2340	-20500
Snake	Q3	2360	-21000
Snake	Q3	2380	-21500
Snake	Q3	2400	-22000
Snake	Q3	2420	-22500
Snake	Q3	2440	-23000
Snake	Q3	2460	-23500
Snake	Q3	2480	-24000
Snake	Q3	2500	-24500
Snake	Q3	2520	-25000
Snake	Q3	2540	-25500
Snake	Q3	2560	-26000
Snake	Q3		

In Figure 16, a graph similar to Figure 14 can be seen. As per this previous figure, the radius represents a character's unique player base with the x representing matches and y representing elo gained meaning that the closer to the top right that a bubble is, the better performing that

character is. The only difference between this chart and Figure 14, is that each bubble now represents a character within a quarter which is why each maximum axis is approximately 1/4 that of Figure 14's.

Previously seen within Figure 14 was that of Snake, Palutena, Wolf and Joker performing well within 2019. This trend of well performing characters has managed to stay mostly consistent with the exception of Palutena. Previously, Palutena was second as the best performing character behind Snake but has been overtaken by Joker within this figure. It's also evident that Palutena lacks results from Q2. This may be because many players stopped playing the character due to Joker's release, as seen previously in the character analysis section (Figure 6).

The strongest performance seen within this graph is that of Snake during Q1. While Snake did appear within the Character Analysis graphs, he was never a top 5 picked character meaning that the majority of Snake players performed very well at a high level and were active which resulted in Snake having the best performance for Q1 2019.

To get a full grasp of performance, I once again decided to get the top 25 most played characters in their quarters. This also removed overlapping datapoints as it was not visually pleasing.

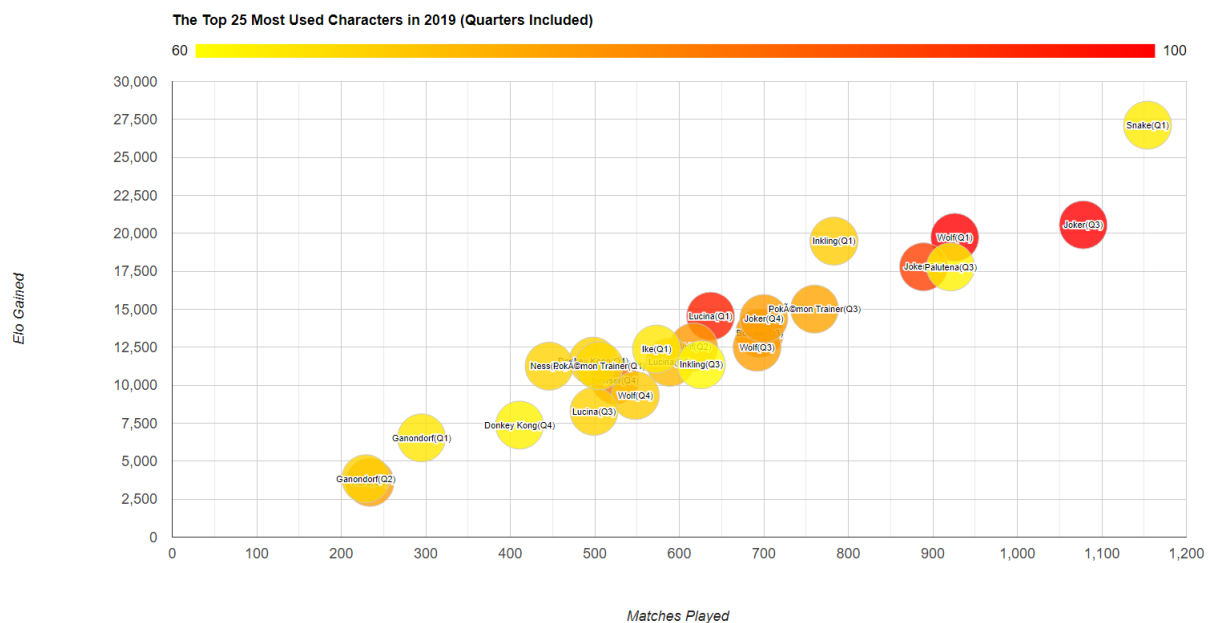


Figure 17: Top 25 Character Usage Throughout 2019 Quarters

This graph demonstrates a selected top amount of characters with unique player usage being represented in colours which can be seen in the gradient legend above the graph.

As per the character data analysis, it was expected that the Joker and Wolf would have the highest player amounts which can be seen by their bright red colours. It's very interesting to note that Snake had a very small playerbase within Q1 but still remains very active and well performing character.

It's also worth looking at the matches played difference between Joker (Q3) and Snake's (Q1). They have a small gap of matches played but have a larger elo gain difference between them. A reason for this may be that Joker players in Q3 did not have a majority of high level players but rather a mix of different skill level players where as Snake players in Q1 may have consisted of high level players which would explain the difference in elo gained.

5 Self Evaluation & Summary of Findings

Overall, I was able to find some very interesting points such as how QLD performs better than NSW and how matches played directly correlates to elo gain. It was also interesting to see the most played characters within each quarter.

If I was to take this project further, I would add elo loss and factor in negative elo loss. I would also try to use another graphing software other than Google Charts as limited to what the library could do and felt rather tedious at times to use.

As I stated in the beginning, I wanted to find answers to these questions, I believe I was able to find these answers through my visualisations:

1. Does the amount of players influence the elo gain?
2. Do more players mean better results?
3. What is the relation between top played characters and elo gain?
4. How did character usage change between each quarter?
5. Which state performed the best in which quarter?
6. Which quarter had the best performance?

1. The amount of players did influence elo gain. This could be seen within the mixed data analysis section.
2. More players do not always mean better results. These factors were found in the mixed data analysis section with obvious outliers and was due to top players influencing elo gain.
3. Top played characters usually had the most elo gain but not always, similar to the previous statement, good players would 'carry' the small playerbase for their character.
4. As seen in the character analysis section, top played characters such as Lucina, Wolf and Joker remained as the top most played. Whenever a new character was added, they were usually popular within their quarter.
5. The elo analysis section showed which state performed best in which quarter. Q1 - VIC, Q2 - Q4 was QLD.
6. The quarter that had the best performance was in Q1 as seen in the mixed analysis section.

If you would like to look further into character analysis or interact with the graphs to see more exact values. You are welcome to load up [graphChoice.html](#) in the Visualisation Project and pick a graph you would like to look at. I would suggest looking at the bar graphs as they are interactive and give further insight into character usage within states rather than the whole of Australia.

Thanks for reading, Nat