

Python-to-R-Apex

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Overview

The data set used for this analysis is based on the game Apex Legends. I collected the data myself, over the course of 30+ weeks using the stats provided by the game at the end of every match. The same three players are the only three players in the data. Only games where we placed top 5 are included. Since I collected it myself, there should be no need for any pre-processing. The goal is get an intermediate analysis from our games to see what works best and what may not work the best.

Evaluation may be used using regression models or tree based methods.

Explanation of the variables in the dataset:

- djdmg, popdmg, spoondmg: The amount of damage each user accumulated during the match
- djkill, popkill, spoonkill: The amount of kills each user accumulated during the match
- location: The map the match was played on. There are three maps used in this rotation; World's Edge (WE), Olympus (OL), and Kings Canyon (KC)
- dlegend, plegend, slegend: The legend each user used during that match
- placing: The placement we received at the end of the match. This number is 1-5
- date: Calendar date the match was played on
- day: Calendar day the match was played on
- mode: The game mode the match was played on. This is either ranked or pub (public)

Load data into R

```
data <- read.csv("apex2022.csv")

# dropping columns
data <- data[, !(names(data) %in% c('Time.of.Day', 'Week', 'X'))]

# lowercase column names
names(data) <- tolower(names(data))

# standardize mode
data$mode <- tolower(trimws(data$mode))

head(data)
```

```
##   djdmg djkill popdmg popkill spoondmg spoonkill location   dlegend plegend
## 1    738      2    670      0      269         1      WE Pathfinder Lifeline
```

```
## 2 1158      4 1701      4      833      4      WE Pathfinder Lifeline
## 3  896      0 1117      5     1014      3      WE      Wraith      Loba
## 4  367      1  931      4      680      1      WE      Wraith Lifeline
## 5  227      1  172      1      678      1      WE      Wattson Lifeline
## 6  938      3 1359      5     1054      6      WE      Wattson      Wraith
##  slegend placing  date      day  mode
## 1 Octane        1 23-Dec Wednesday ranked
## 2 Octane        2 23-Dec Wednesday ranked
## 3 Crypto        1 24-Dec Thursday ranked
## 4 Crypto        2 24-Dec Thursday ranked
## 5 Octane        5 24-Dec Thursday ranked
## 6 Octane        1 24-Dec Thursday ranked
```

After loading the data, I got rid of the columns ‘Time of Day’ and ‘Week’ and also lowercased the column names.

Check data

```
# fix wrong capitalization
data$dlegend <- ifelse(data$dlegend == 'Gibraltar', 'Gibraltar', data$dlegend)

# count null values
print(colSums(is.na(data)))
```

```
##      djdmg      djkill      popdmg      popkill      spoondmg      spoonkill      location      dlegend
##           0           0           0           0           0           0           0           0
##      plegend      slegend      placing      date      day      mode
##           0           0           0           0           0           0
```

```
# describe data
summary(data)
```

```
##      djdmg      djkill      popdmg      popkill
## Min.   : 9.0   Min.   : 0.000   Min.   : 0   Min.   :0.000
## 1st Qu.: 574.0 1st Qu.: 1.000   1st Qu.: 318 1st Qu.:0.000
## Median : 866.0 Median : 2.000   Median : 549 Median :1.000
## Mean   : 909.5 Mean   : 2.307   Mean   : 597 Mean   :1.775
## 3rd Qu.:1156.5 3rd Qu.: 3.000   3rd Qu.: 799 3rd Qu.:3.000
## Max.   :3193.0 Max.   :11.000   Max.   :2100 Max.   :8.000
##      spoondmg      spoonkill      location      dlegend
## Min.   : 0.0   Min.   : 0.00   Length:515   Length:515
## 1st Qu.: 542.0 1st Qu.: 1.00   Class :character   Class :character
## Median : 828.0 Median : 2.00   Mode  :character   Mode  :character
## Mean   : 890.1 Mean   : 2.61
## 3rd Qu.:1188.5 3rd Qu.: 4.00
## Max.   :3091.0 Max.   :12.00
##      plegend      slegend      placing      date
## Length:515   Length:515   Min.   :1.000   Length:515
## Class :character   Class :character   1st Qu.:1.000   Class :character
## Mode  :character   Mode  :character   Median :2.000   Mode  :character
##                               Mean   :2.489
```

```
##                               3rd Qu.:3.000
##                               Max.    :5.000
##      day                      mode
## Length:515                  Length:515
## Class :character            Class :character
## Mode  :character            Mode  :character
##
##
##
```

There was a wrongly capitalized legend name in the data when I checked it, so that had to be corrected. Everything else looked normal. No null values either.

User-Legend data analysis

Usage per user, per legend

```
legend_counts <- list()
legend_columns <- c('dlegend', 'plegend', 'slegend')

for (column in legend_columns) {
  counts <- table(data[[column]])
  legend_counts[[column]] <- counts
}

for (column_name in names(legend_counts)) {
  cat("Player:", column_name, "\n")
  print(legend_counts[[column_name]])
}
```

```
## Player: dlegend
##
## Bloodhound    Caustic      Crypto      Fuse  Gibraltar  Horizon  Lifeline
##           24         3         6         3         95         94         22
##      Mirage    Octane Pathfinder  Revenant  Valkyrie  Wattson  Wraith
##           11        10       112        54         2         21         58
## Player: plegend
##
## Bangalore Bloodhound      Crypto  Gibraltar  Lifeline      Loba      Mirage
##           3         189         3         7         140        11         7
##      Octane Pathfinder  Rampart  Revenant  Valkyrie  Wattson  Wraith
##           7         4         2        10         71        38        23
## Player: slegend
##
## Bangalore    Caustic      Crypto      Fuse  Gibraltar  Mirage      Octane
##           75         29         26         6         1         7        342
## Pathfinder  Revenant      Seer  Valkyrie  Wattson  Wraith
##           3         10        10         3         1         2
```

DJ used Pathfinder the most, Pop used Bloodhound the most, and Spoon used Octane a ton. This may cause outliers in some parts of the data.

Highest damage per user, per legend

##	dlegend	djdmg
## 10	Pathfinder	3193
## 3	Crypto	2378
## 14	Wraith	2323
## 5	Gibraltar	2269
## 6	Horizon	2129
## 13	Wattson	2013
## 7	Lifeline	2007
## 11	Revenant	1848
## 8	Mirage	1710
## 1	Bloodhound	1616
## 9	Octane	1345
## 12	Valkyrie	1196
## 4	Fuse	1059
## 2	Caustic	711

##	plegend	popdmg
## 12	Valkyrie	2100
## 5	Lifeline	1865
## 2	Bloodhound	1651
## 13	Wattson	1593
## 8	Octane	1439
## 14	Wraith	1428
## 4	Gibraltar	1415
## 6	Loba	1281
## 11	Revenant	974
## 9	Pathfinder	832
## 7	Mirage	747
## 3	Crypto	693
## 1	Bangalore	581
## 10	Rampart	544

##	slegend	spoondmg
## 1	Bangalore	3091
## 7	Octane	2458
## 9	Revenant	2446
## 2	Caustic	2362
## 3	Crypto	2330
## 10	Seer	1940
## 11	Valkyrie	1704
## 6	Mirage	1686
## 8	Pathfinder	1431
## 5	Gibraltar	1394
## 4	Fuse	1075
## 13	Wraith	921
## 12	Wattson	506

Despite using Octane an extreme amount, Spoon actually has his highest damage with Bangalore. Pop's highest damage is Valkyrie, with Bloodhound ranking 3rd.

Highest kills per user, per legend

```
##      dlegend dkill
## 10 Pathfinder    11
## 14   Wraith      9
## 1  Bloodhound    8
## 5   Gibraltar    7
## 6   Horizon      7
## 3    Crypto      6
## 7   Lifeline     6
## 9    Octane      6
## 11  Revenant     6
## 12  Valkyrie     6
## 13  Wattson      6
## 8   Mirage       5
## 2   Caustic      3
## 4    Fuse        2
##      plegend popkill
## 12  Valkyrie     8
## 5   Lifeline     7
## 13  Wattson      7
## 2  Bloodhound    6
## 4   Gibraltar    6
## 6    Loba        5
## 8    Octane      5
## 11  Revenant     5
## 14  Wraith       5
## 1  Bangalore     4
## 3    Crypto      3
## 7    Mirage      3
## 9  Pathfinder    3
## 10  Rampart      1
##      slegend spoonkill
## 2   Caustic     12
## 7    Octane     11
## 1  Bangalore     9
## 10   Seer        7
## 8  Pathfinder    6
## 9   Revenant     6
## 3    Crypto      5
## 5   Gibraltar    5
## 11  Valkyrie     5
## 4    Fuse        4
## 6    Mirage      4
## 13  Wraith       3
## 12  Wattson      2
```

Again, despite being a popular character for Spoon, his Octane fell short from having the highest kills and damage stat from his pool of characters. DJ's Pathfinder remains consistent in highest damage and kill stat from his pool of characters.

Summation data per user, per legend

```
##      dlegend djdmg djkill
## 10 Pathfinder 96862   263
##  5  Gibraltar 92667   211
##  6   Horizon 85419   192
## 11  Revenant 54347   148
## 14   Wraith 49546   133
##  7  Lifeline 21627    60
##  1 Bloodhound 20240    56
## 13   Wattson 19240    48
##  8   Mirage  8387    30
##  9   Octane  8001    20
##  3   Crypto  6670    15
##  4    Fuse  2119     2
## 12  Valkyrie 1690     6
##  2   Caustic 1583     4
##      plegend popdmg popkill
##  2 Bloodhound 108984   332
##  5  Lifeline  86194   254
## 12  Valkyrie  47951   130
## 13   Wattson  21185    65
## 14   Wraith  11962    34
##  6    Loba   6870    20
##  4  Gibraltar  6161    22
## 11  Revenant  5620    18
##  8   Octane  4468    14
##  7   Mirage  2472    10
##  9 Pathfinder  2375     6
##  3   Crypto  1521     3
##  1 Bangalore   850     4
## 10  Rampart   833     2
##      slegend spoondmg spoonkill
##  7   Octane  305296   898
##  1 Bangalore  72213   202
##  2   Caustic  25151    76
##  3   Crypto  18228    47
##  9  Revenant  10181    30
## 10    Seer   8684    31
##  6   Mirage  5964    16
## 11  Valkyrie  3484    13
##  4    Fuse  3338    11
##  8 Pathfinder  2281     9
## 13   Wraith  1656     4
##  5  Gibraltar  1394     5
## 12   Wattson   506     2
```

What is shown here is each players summed kills and damage with each character they play. Spoon's Octane usage finally shows here, with almost double as much damage and kills on one character than Pop and DJ's top legend combined.

Each users best legend

##		dlegend	djdmg	djkill
## 10	Pathfinder	3193		11
## 3	Crypto	2378		6
## 14	Wraith	2323		9
## 5	Gibraltar	2269		7
## 6	Horizon	2129		7
## 13	Wattson	2013		6
## 7	Lifeline	2007		6
## 11	Revenant	1848		6
## 8	Mirage	1710		5
## 1	Bloodhound	1616		8
## 9	Octane	1345		6
## 12	Valkyrie	1196		6
## 4	Fuse	1059		2
## 2	Caustic	711		3

##		plegend	popdmg	popkill
## 12	Valkyrie	2100		8
## 5	Lifeline	1865		7
## 2	Bloodhound	1651		6
## 13	Wattson	1593		7
## 8	Octane	1439		5
## 14	Wraith	1428		5
## 4	Gibraltar	1415		6
## 6	Loba	1281		5
## 11	Revenant	974		5
## 9	Pathfinder	832		3
## 7	Mirage	747		3
## 3	Crypto	693		3
## 1	Bangalore	581		4
## 10	Rampart	544		1

##		slegend	spoondmg	spoonkill
## 1	Bangalore	3091		9
## 7	Octane	2458		11
## 9	Revenant	2446		6
## 2	Caustic	2362		12
## 3	Crypto	2330		5
## 10	Seer	1940		7
## 11	Valkyrie	1704		5
## 6	Mirage	1686		4
## 8	Pathfinder	1431		6
## 5	Gibraltar	1394		5
## 4	Fuse	1075		4
## 13	Wraith	921		3
## 12	Wattson	506		2

If you look at the MAX damage and kills to see the best legend for each user, it looks to be what you expect. Let's check what would happen if we took the average.

Each users best legend (by average)

```
# calculate the averages and counts for each legend for dj
best_legend_dj_avg <- data %>%
  group_by(dlegend) %>%
  summarise(
    avg_dj_dmg = mean(djdmg),
    avg_dj_kill = mean(djkill),
    count = n()
  ) %>%
  filter(count > 20) %>% # filter out legends with less than 20 uses since we're taking average
  arrange(desc(avg_dj_dmg), desc(avg_dj_kill))

# calculate the averages and counts for each legend for pop
best_legend_pop_avg <- data %>%
  group_by(plegend) %>%
  summarise(
    avg_pop_dmg = mean(popdmg),
    avg_pop_kill = mean(popkill),
    count = n()
  ) %>%
  filter(count > 20) %>% # filter out legends with less than 20 uses since we're taking average
  arrange(desc(avg_pop_dmg), desc(avg_pop_kill))

# calculate the averages and counts for each legend for spoon
best_legend_spoon_avg <- data %>%
  group_by(slegend) %>%
  summarise(
    avg_spoon_dmg = mean(spoondmg),
    avg_spoon_kill = mean(spoonkill),
    count = n()
  ) %>%
  filter(count > 20) %>% # filter out legends with less than 20 uses since we're taking average
  arrange(desc(avg_spoon_dmg), desc(avg_spoon_kill))

print(best_legend_dj_avg)
```

```
## # A tibble: 8 x 4
##   dlegend      avg_dj_dmg avg_dj_kill count
##   <chr>          <dbl>      <dbl> <int>
## 1 Revenant      1006.        2.74    54
## 2 Lifeline       983.        2.73    22
## 3 Gibraltar     975.        2.22    95
## 4 Wattson       916.        2.29    21
## 5 Horizon       909.        2.04    94
## 6 Pathfinder     865.        2.35   112
## 7 Wraith        854.        2.29    58
## 8 Bloodhound     843.        2.33    24
```

```
print(best_legend_pop_avg)
```

```
## # A tibble: 5 x 4
```



```
##   plegend      avg_pop_dmg avg_pop_kill count
##   <chr>          <dbl>          <dbl> <int>
## 1 Valkyrie        675.            1.83    71
## 2 Lifeline        616.            1.81   140
## 3 Bloodhound      577.            1.76   189
## 4 Wattson         558.            1.71    38
## 5 Wraith          520.            1.48    23
```

```
print(best_legend_spoon_avg)
```

```
## # A tibble: 4 x 4
##   slegend      avg_spoon_dmg avg_spoon_kill count
##   <chr>          <dbl>          <dbl> <int>
## 1 Bangalore      963.            2.69    75
## 2 Octane          893.            2.63   342
## 3 Caustic         867.            2.62    29
## 4 Crypto          701.            1.81    26
```

Interestingly enough, the best legend didn't change for anybody except for DJ, with Revenant shooting up multiple placements vs his placement using the max damage and kills. It could be due to Pathfinder having double the game count than Revenant. Regardless, Pathfinder will still be counted as DJ's best legend.

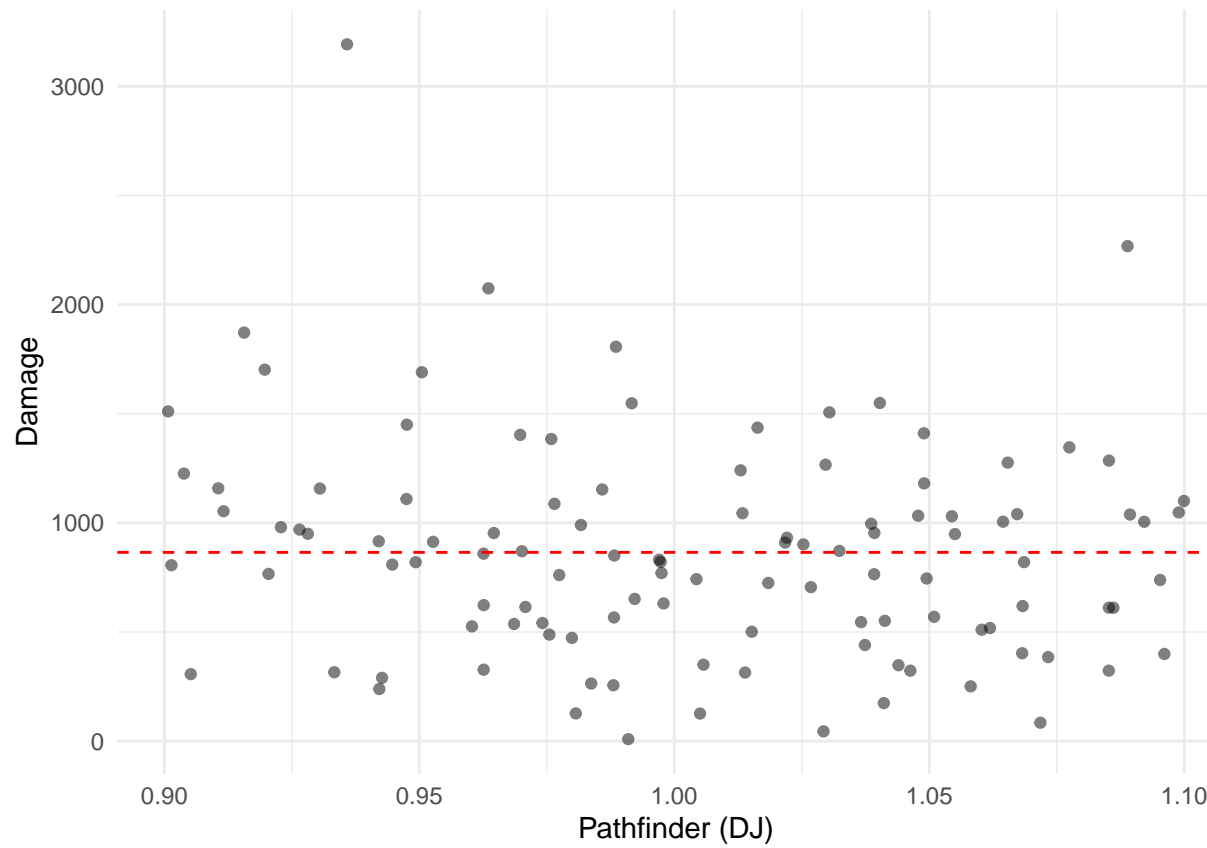
Best Legend (by Win Rate)

```
## Win rates for dlegend :
##
## Bloodhound      Caustic      Crypto      Fuse Gibraltar Horizon Lifeline
## 0.16666667 0.00000000 0.33333333 0.00000000 0.28421053 0.27659574 0.36363636
##   Mirage      Octane Pathfinder Revenant Valkyrie Wattson Wraith
## 0.09090909 0.20000000 0.31250000 0.27777778 0.00000000 0.28571429 0.29310345
##
## Win rates for plegend :
##
## Bangalore Bloodhound      Crypto Gibraltar Lifeline      Loba      Mirage
## 0.00000000 0.2910053 0.00000000 0.2857143 0.2785714 0.2727273 0.1428571
##   Octane Pathfinder Rampart Revenant Valkyrie Wattson Wraith
## 0.1428571 0.0000000 0.0000000 0.2000000 0.2816901 0.4210526 0.1739130
##
## Win rates for slegend :
##
## Bangalore      Caustic      Crypto      Fuse Gibraltar Mirage      Octane
## 0.26666667 0.3103448 0.2307692 0.16666667 1.0000000 0.1428571 0.3011696
## Pathfinder Revenant      Seer Valkyrie Wattson Wraith
## 0.00000000 0.0000000 0.1000000 0.3333333 0.0000000 0.0000000
```

Win rate for each legend was found by finding the number of wins a user has with that legend divided by the total number of times the legend was used by that user. Going by win rate alone, Lifeline is DJ's best, Wattson is Pop's best, and Gibraltar (he only had one game where he won on Gibraltar) or Valkyrie is Spoon's best.

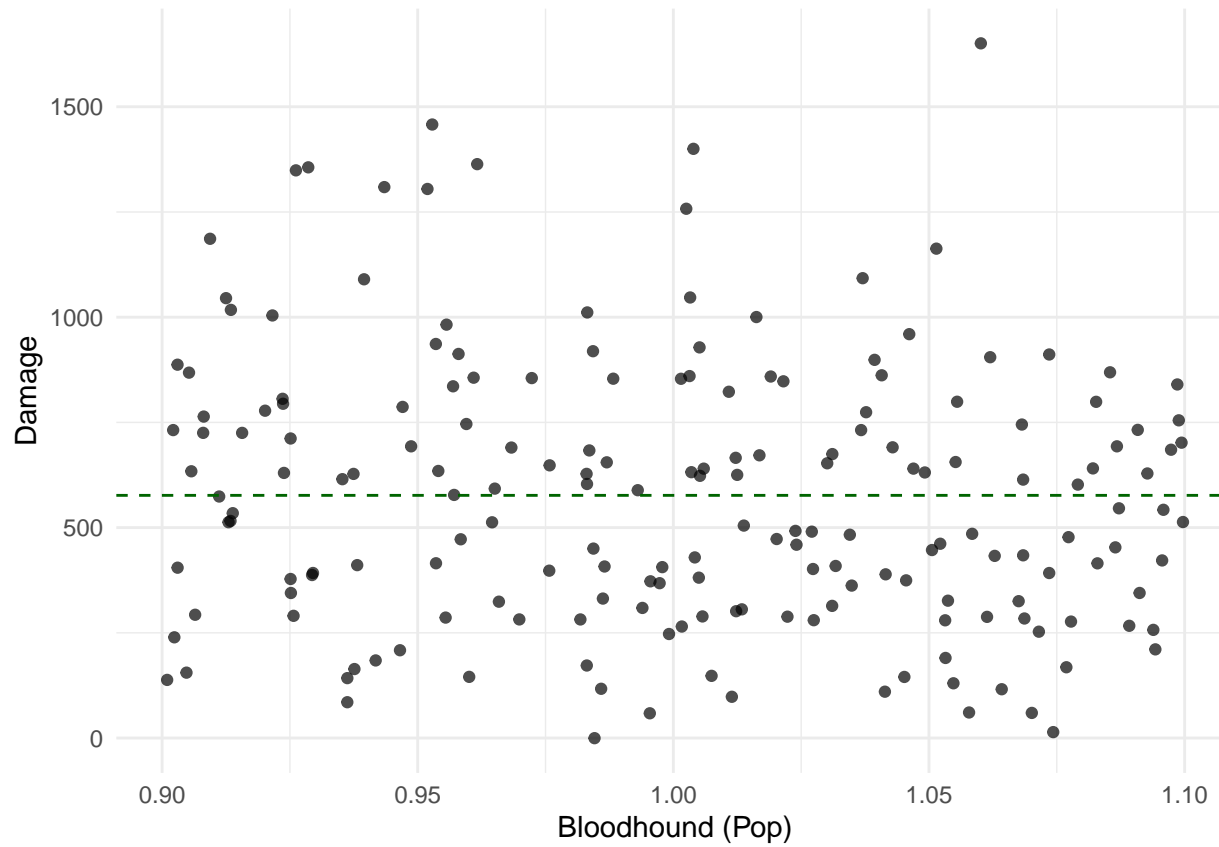
Plotting data

Plotting each players best legend



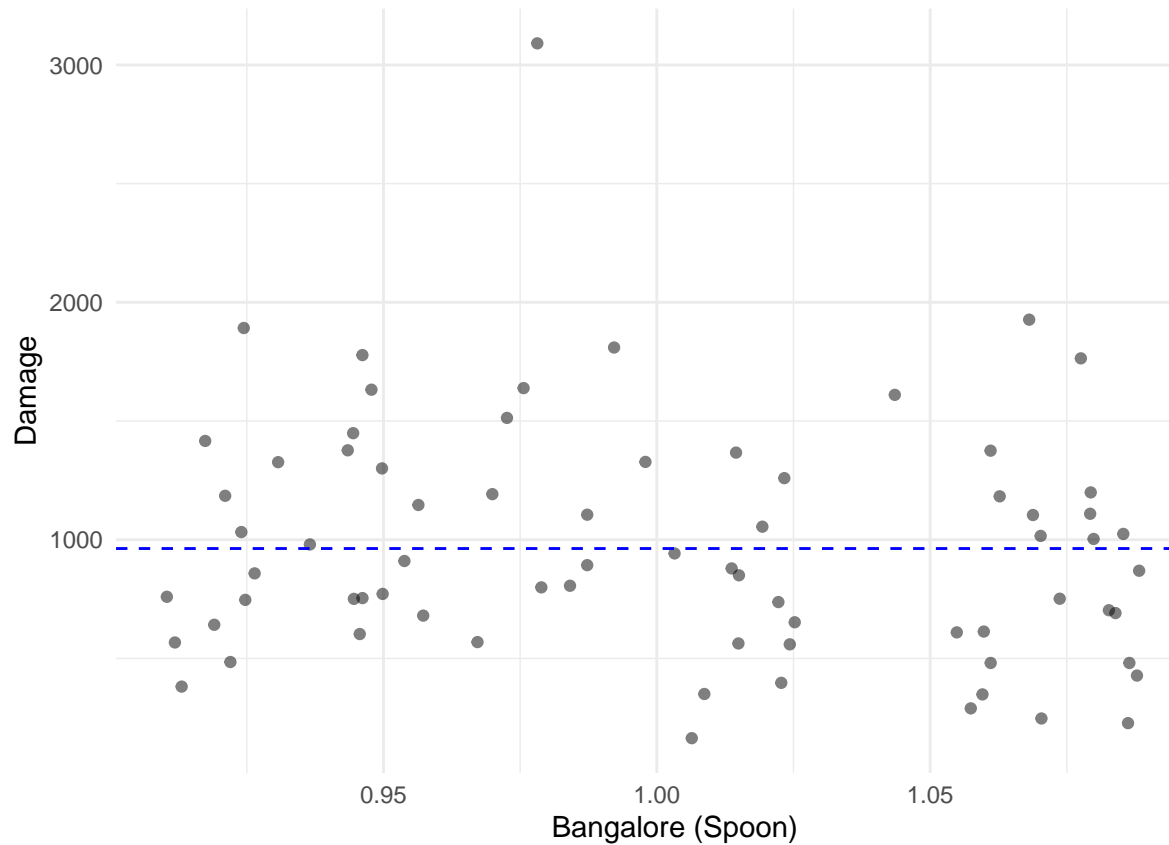
DJ's Pathfinder

Most of DJ's Pathfinder damage falls along the average, with a few outliers.



Pop's Valkyrie

Pop's damage with Bloodhound looks like it's more prone to having outliers, where less of Pop's games fall along the average.



Spoon's Bangalore

Spoon's damage seems to be consistent with the average, not shooting too far above or below it.

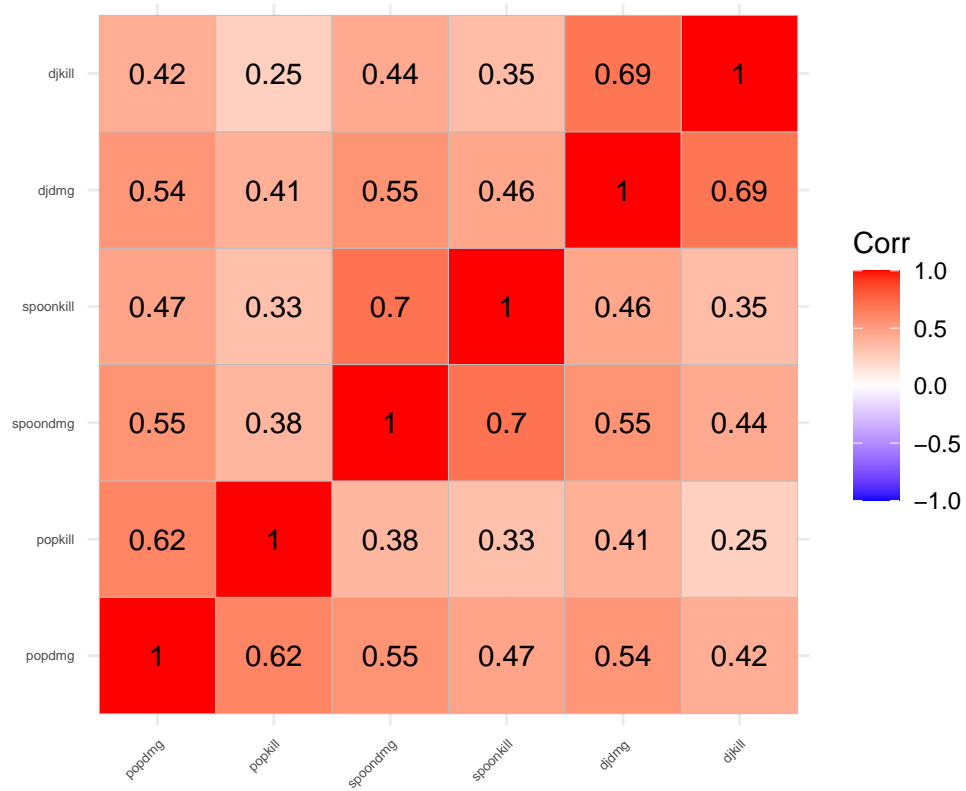
Correlation matrix plot

```
# get the numeric columns for the correlation matrix
numeric_data <- data[c('djdmg', 'djkill', 'popdmg', 'popkill', 'spoondmg', 'spoonkill')]

# calculate correlation matrix
corr_matrix <- cor(numeric_data)

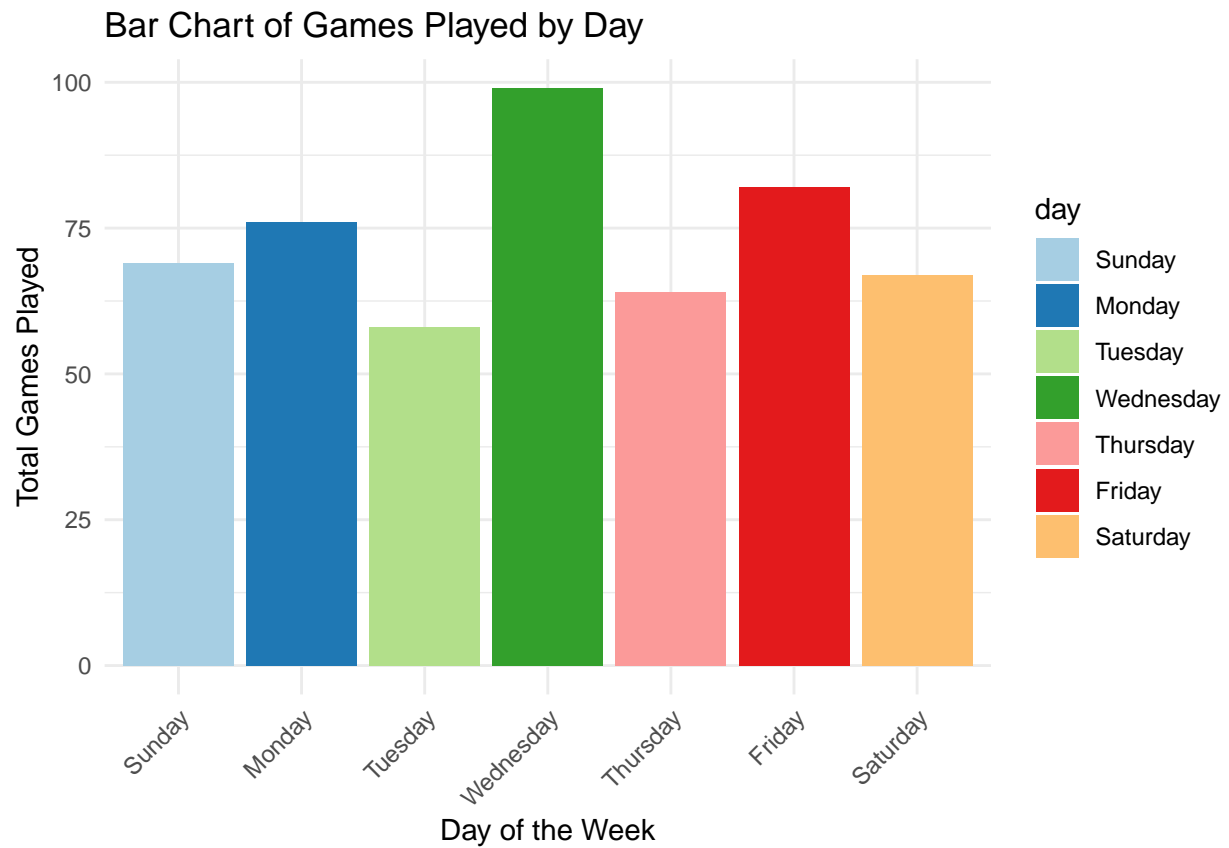
# plot matrix
ggcorrplot(corr = corr_matrix, lab_size = 4, tl.cex = 5,
            lab = T, title = "Correlation heatmap", hc.order = T)
```

Correlation heatmap



It looks like each players kills and damage alike is positively correlated with themselves, but there isn't much correlation between each players kills and damage with another player. Not much what I was expected, I figured if one player did good in one game, then the other 2 would also do somewhat good.

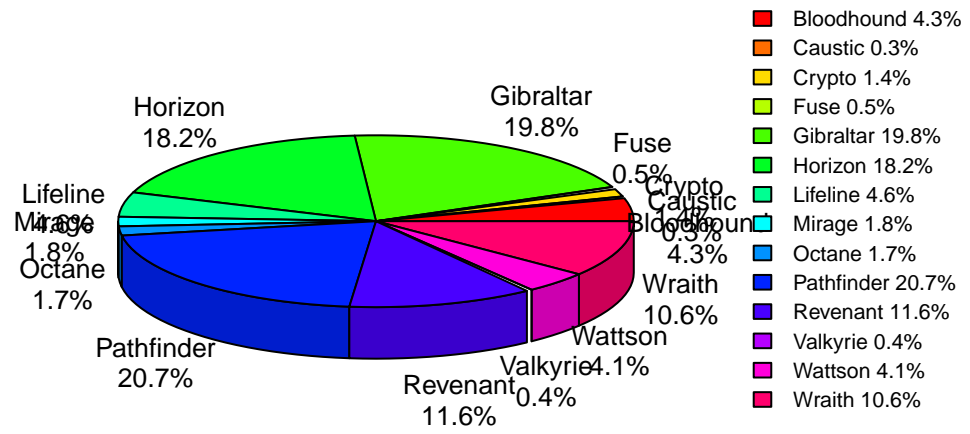
What days of the week did we play most?



```
## $day
## [1] "Wednesday"
##
## $count
## [1] 30
```

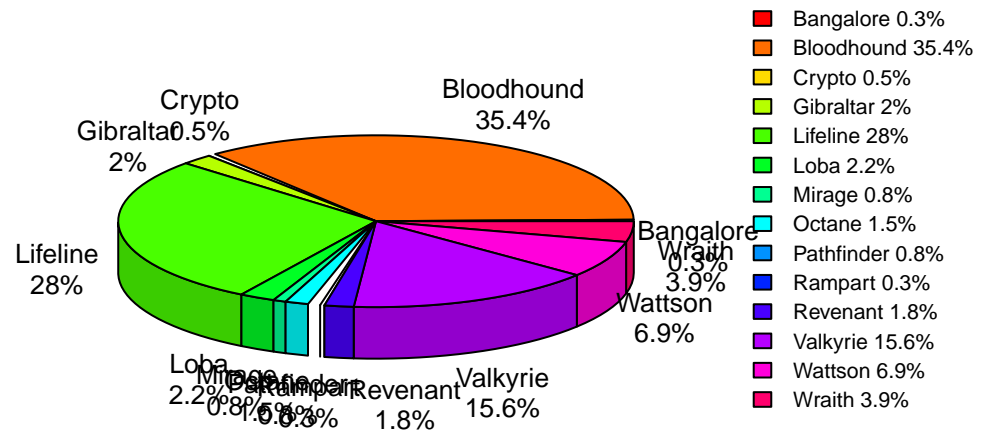
I guess Wednesday was our most commonly played day. We also got the most 1st places on Wednesday as well (30)

Dj Damage Distribution by Legend



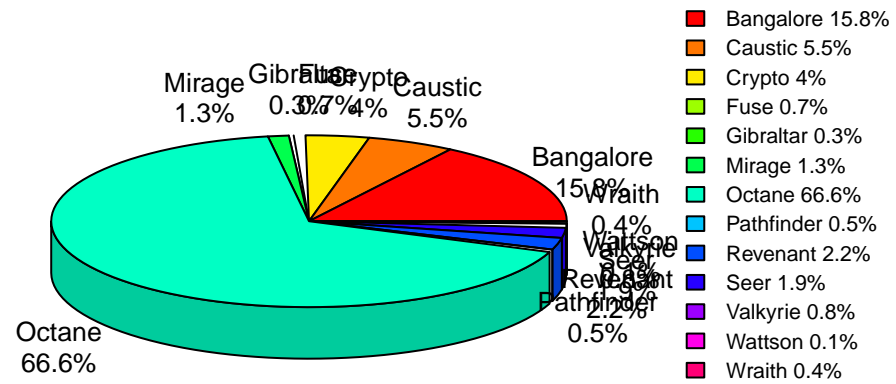
DJ has 3 characters that total about 60% of the damage distribution. Horizon, Pathfinder, and Gibraltar.

Pop Damage Distribution by Legend



Popshot has 2 characters that account for about 60% of the damage distribution. Bloodhound and Lifeline.

Spoon Damage Distribution by Legend

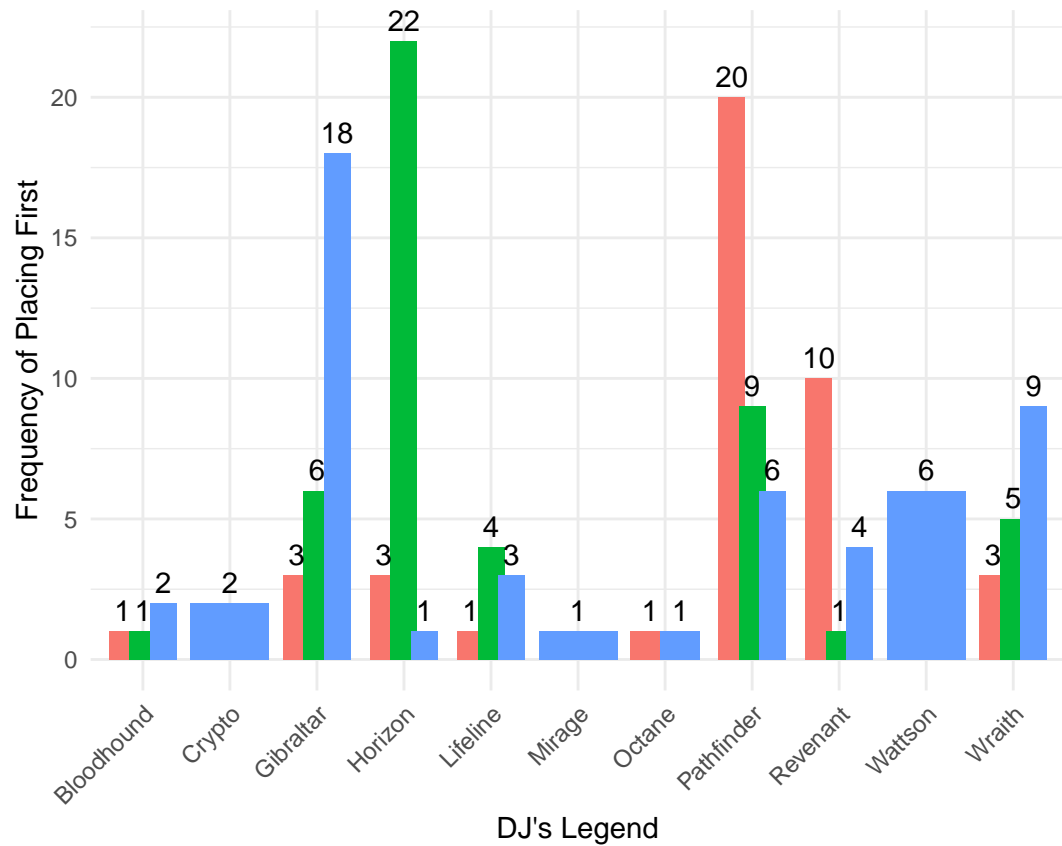


Spoon results were easy to spot from a mile away, seeing the number of games on Octane from earlier.

When do we win?

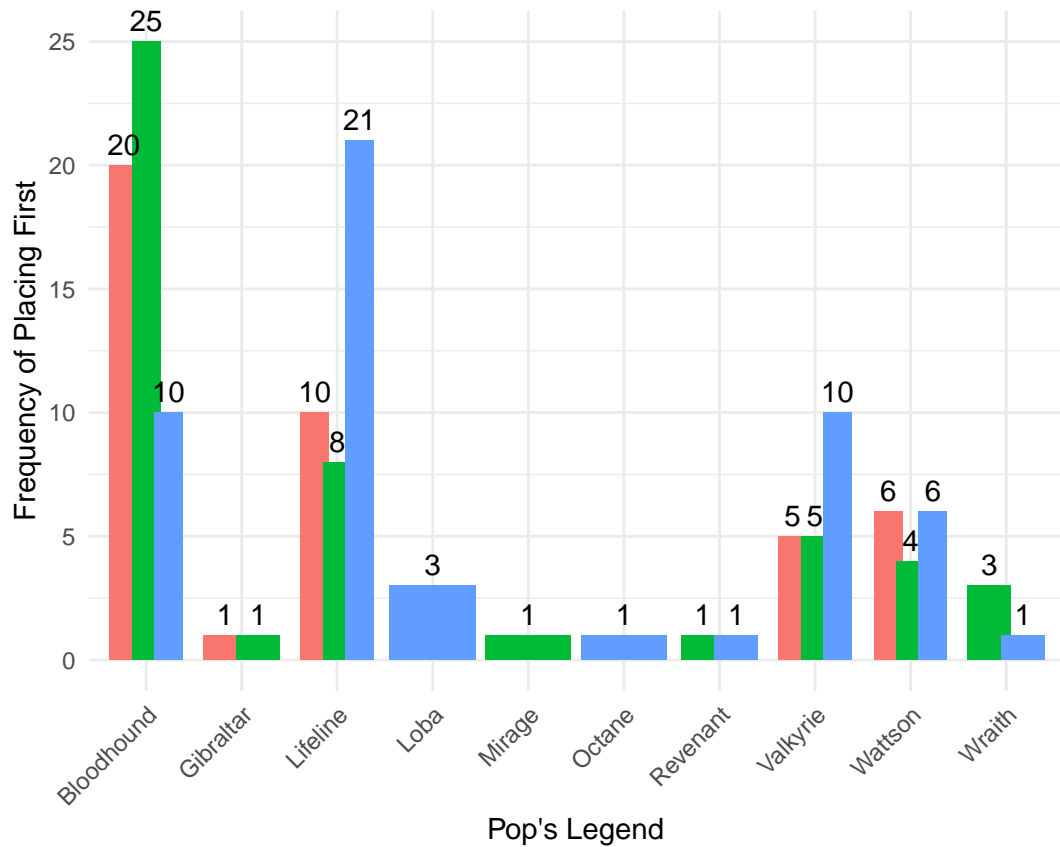
Here we will focus on what the scenario is when we win. Is it a specific character for each player, or maybe a team of 3 specific legends.

First place frequencies



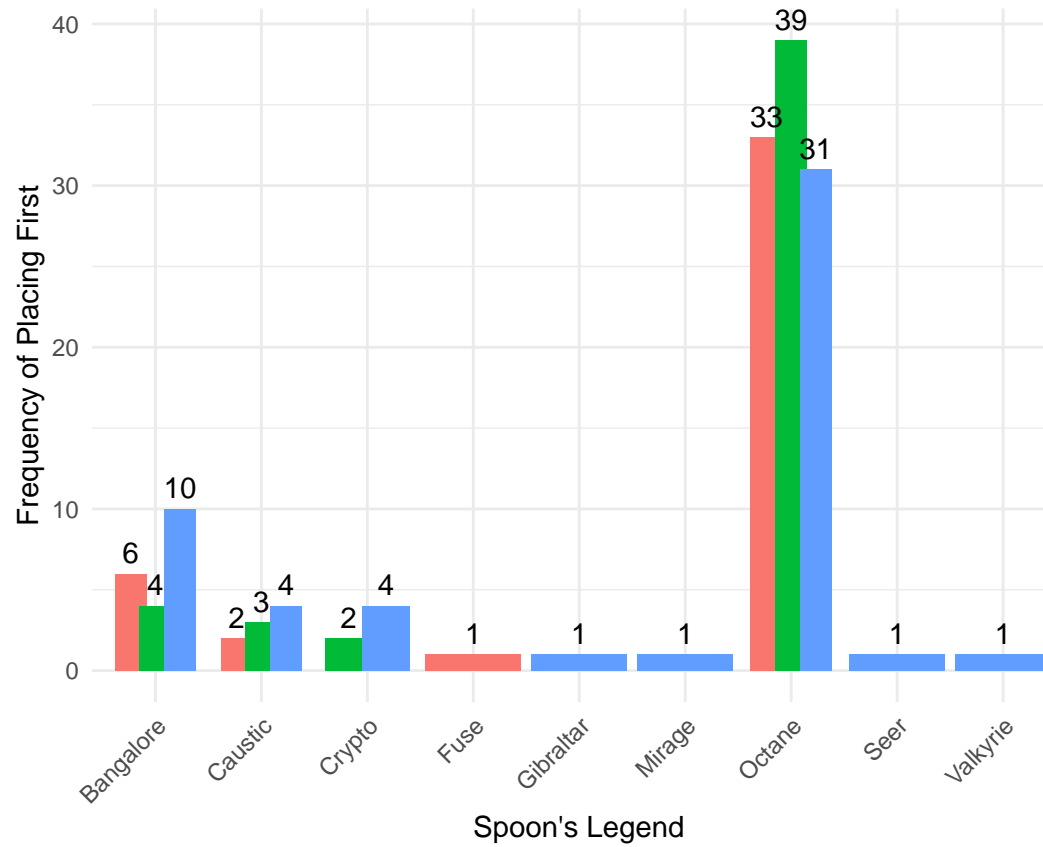
DJ First place frequencies

It's clear to see that for DJ had favorites for each respective map. Olympus was a favorite for Horizon, World's Edge was most Gibraltar, and on Kings Canyon we saw more Pathfinder.



Pop First place frequencies

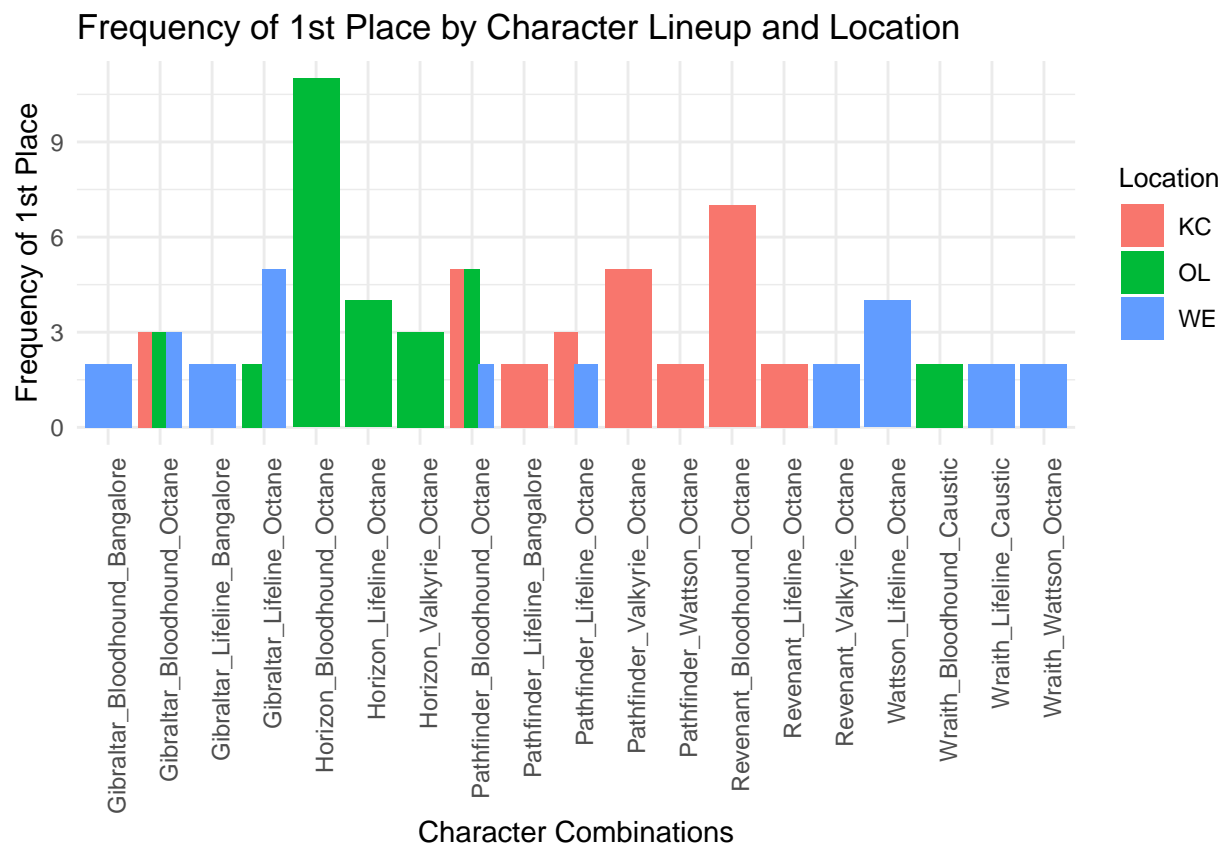
Clearly for Pop, Bloodhound was a fan favorite and a crucial character pick to getting a first place. Lifeline on World's Edge picked up Bloodhound's shortcomings on the map.



Spoon first place frequencies

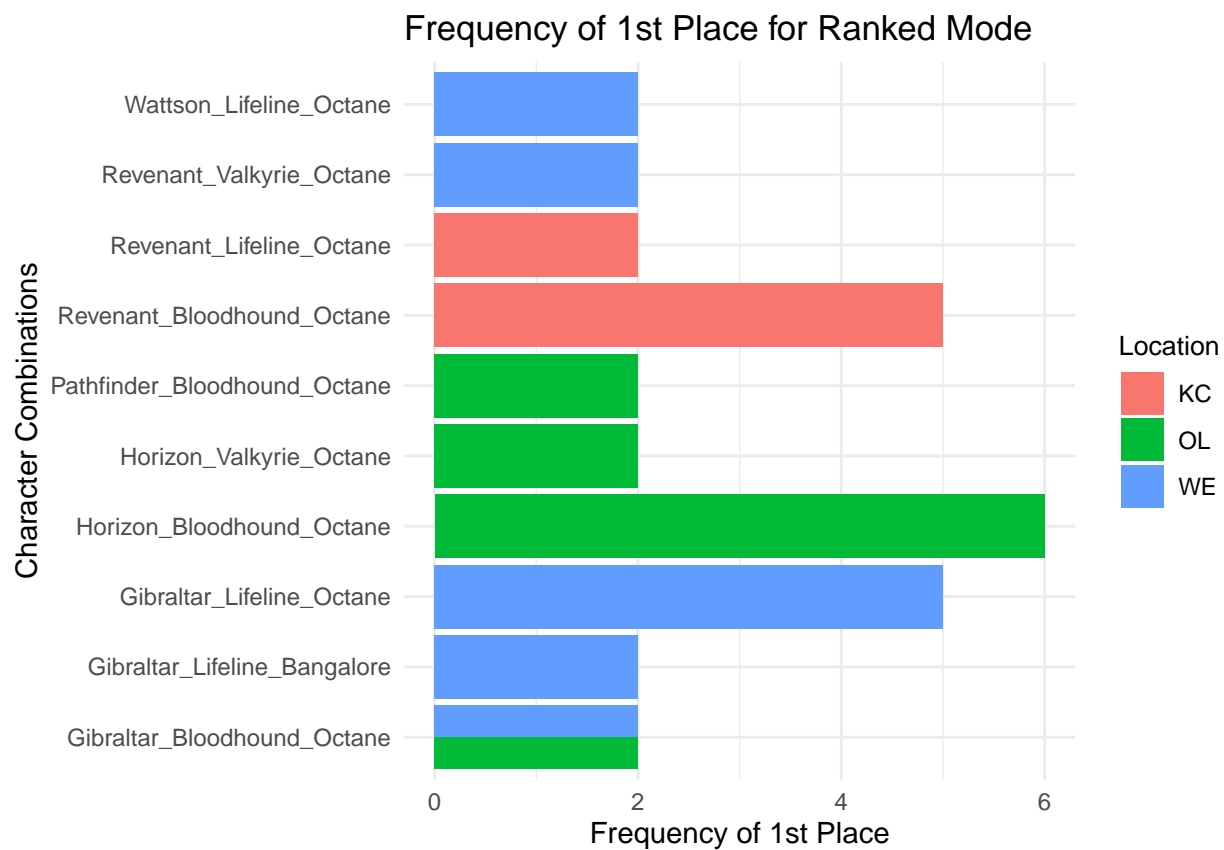
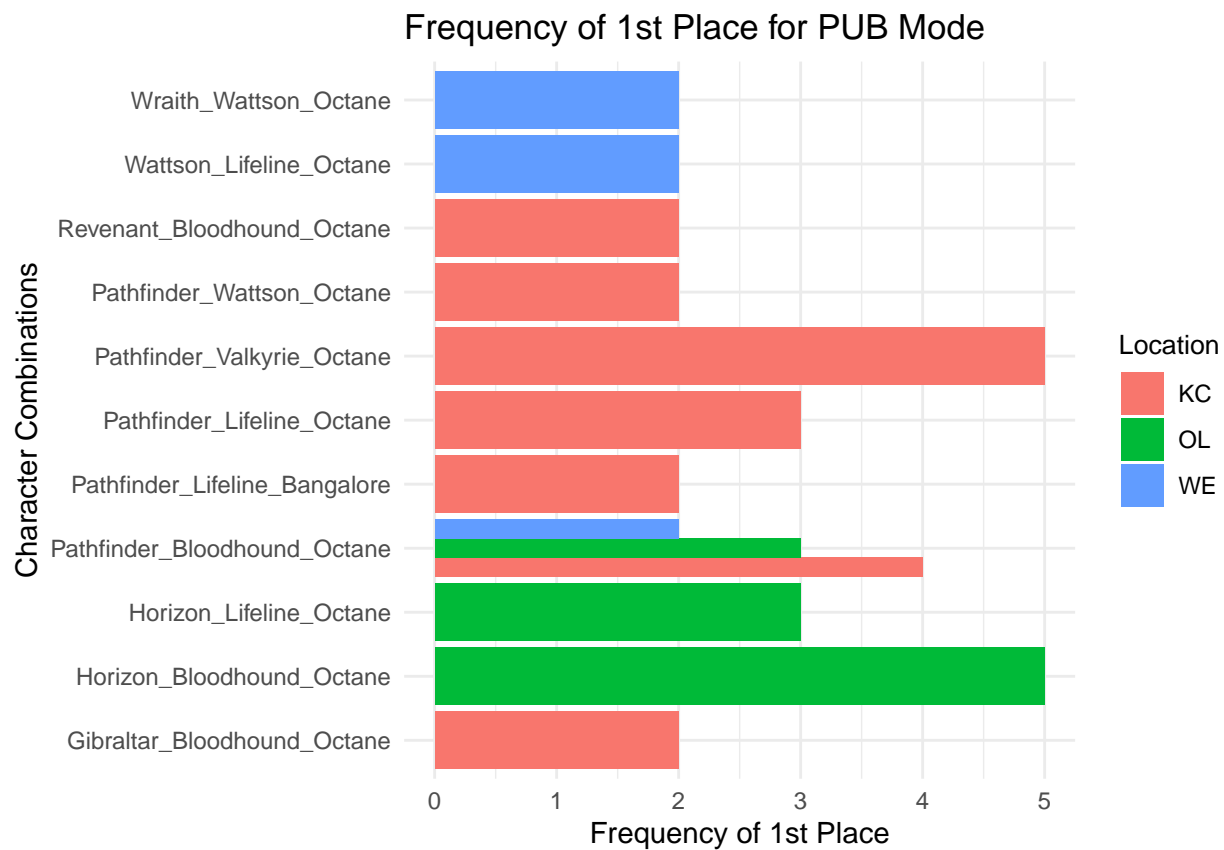
To no one's surprise, Octane was vital to getting a victory on all maps. This is probably due to sheer playtime on Octane though.

What about team combinations?



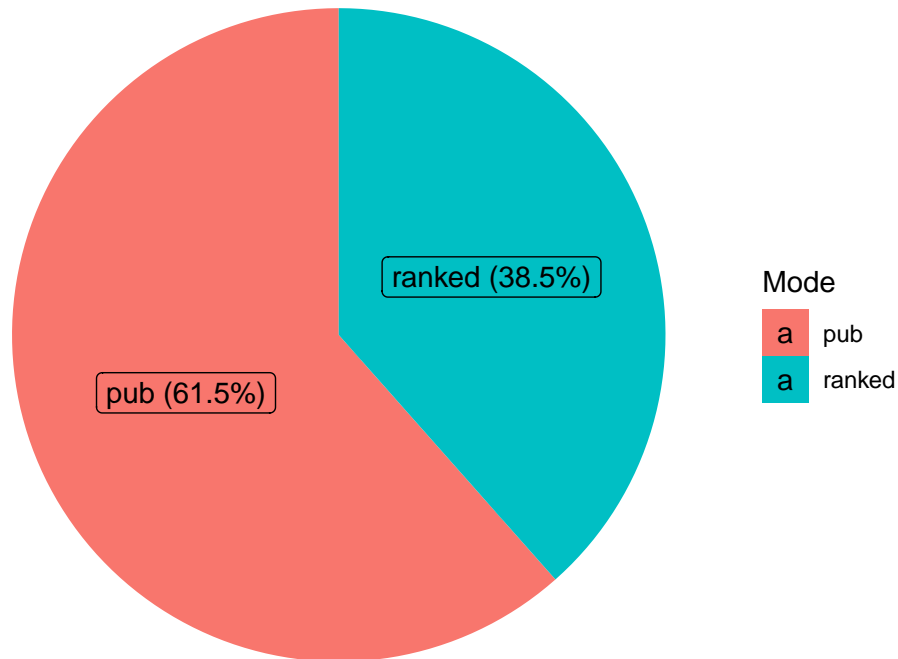
On Olympus the prime trio was Horizon from DJ, Bloodhound from Pop, and Octane from Spoon of course. This might be due to Horizon's strength on Olympus. Interestingly, on Kings Canyon, Revenant from DJ, Bloodhound from Pop, and Octane from Spoon was the best trio on that map. This is explained to due to RevTane meta, where Revenant and Octane on a team meant free kills.

Are we better in ranked or pub matches?



For both modes, it seems like Horizon + Bloodhound + Octane was the all star squad, on Olympus at least.

First place frequencies in PUB vs Ranked mode



```
## # A tibble: 2 x 2
##   mode    count
##   <chr>  <int>
## 1 pub      346
## 2 ranked  169
```

```
## [1] 0.3254438
```

```
## [1] 0.2543353
```

Although the pie chart shows that around 60% of 1st places comes from pubs, and 40% comes from ranked, this could be brushed off as saying pub is easier, but really it is due to the high count of pub matches played. 346 pub matches played, and only 169 ranked matches played. It's arguable to say that we do better in ranked, since we win a higher percentage of ranked games out of all the ranked games played, a 32% win rate, while in pubs our win rate is only 25%.

Scoring

Scoring method - Kill and Damage weighted

```

# define kill and damage weights
kill_weight <- 0.55
damage_weight <- 0.45

# define a list to store scores for each legend
legend_scores <- list()

# list of legend columns and their corresponding kill and damage columns
legend_columns <- c('dlegend', 'plegend', 'slegend')
kill_columns <- c('djkill', 'popkill', 'spoonkill')
damage_columns <- c('djdmg', 'popdmg', 'spoondmg')

# iterate over each legend
for (i in seq_along(legend_columns)) {
  # compute the score for the current legend
  legend_score <- (data[[kill_columns[i]]] * kill_weight) + (data[[damage_columns[i]]] * damage_weight)
  # store the mean of scores divided by 1000 in the list
  legend_scores[[legend_columns[i]]] <- mean(legend_score) / 1000
}

# print
for (legend in names(legend_scores)) {
  cat(paste("Score for", legend, ":", legend_scores[[legend]], "\n"))
}

```

```

## Score for dlegend : 0.41054854368932
## Score for plegend : 0.269618252427184
## Score for slegend : 0.401958058252427

```

The scoring method is pretty simple, we just determined we value kills a bit more than damage, so I gave kills a little more significance when determining the 1st score. There's not much that goes into the score besides kills and damage.

Wrap Up

Wrapping up, I found:

- each users best character
- our best combinations as a team
- each users score based on their overall damage and kills
- our gameplay in ranked vs pub lobbies
- first place frequencies, individually and as a team
- what day of the week we play the most and win the most on
- damage distribution for each user

Next iteration, on top of what is already found here, there will be more variables to look at, such as assists, knocks, revives, respawns, etc as well as Machine Learning techniques like regression or decision trees.