Figure 1: Summoner's Rift

LoL eSports: Clustering Team Roles Milestone Report

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Introduction

To all types of players who play League of Legends (LoL), and to those who watch professionals compete at the game throughout various eSports leagues around the world, it's easy to visually identify the five roles of each competing team in a match.

First of all, by observing each of the players' locations on the map at the beginning of a match one can identify their roles. Figure 1 shows an image of the Summoner's Rift map for reference.

The ***Top Laners*** traverse along dirt path that travels along the west and north perimeters of the map. Near the start of the match they usually combat enemy minions and each other at the northwest corner of the map. This type of combat at the beginning of the match is called the Laning Phase.

The ***Middle (aka Mid) Laners*** traverse along the dirt path that cuts straight across the diagonal of the

map connecting the two opposing bases. They, too, combat enemy minions and each other during the Laning Phase, where they typically compete right at the center of the map.

The ***Bottom Lane (aka Botlane) Carries*** and ***Supports*** traverse along the dirt path that travels along the south and east perimeters of the map. Their laning phase typically occurs at the southeast corner of the map. The ***Botlane Carries*** deliver damage to their opponents and enemy minions, while the ***Supports*** play an auxiliary role by providing protection to their botlane teammates.

Finally, the ***Junglers*** traverse in the forest-like areas between the three lanes. One team's jungle is in the west and south "triangles", while the other team's is in the north and east triangular areas. During the Laning Phase the ***Junglers*** are combating the monsters that inhabit these areas. They may occasionally encounter each other, especially if one Jungler "invades" their opponents' jungle areas.

Therefore, it's nearly as easy to identify team roles in a League of Legends match as it is to identify the nine positions of the defensive players in a baseball game. The botlane is a little trickier, since both ***Carries*** and ***Supports*** are there, but by observing their behaviors during the laning phase the two roles are fairly simple to distinguish.

The Question

Sure, it's easy to identify team roles when observing a single match at a time, but it's not humanly possible to identify team roles for the hundreds, thousands, and millions of matches that have run through Riot Games' servers through eyeballs alone.

Fortunately, Riot Games provides post-match data of teams and individual players for virtually all matches that go through their servers. Is it possible for a machine to take a sample of data from these matches and be able to distinguish all five team roles from each other?

Why the Answering the Question Matters

In the Summoner's Rift game modes for Classic 5v5 matches, Draft Pick and Ranked, because the players' selection of champions are done and revealed in a structured order, team roles are always assigned the same Participant IDs according to which side of the map the players are on:

Table 1: Assumed Team Role Participant IDs – Draft Pick, Ranked, eSports

TeamRole	BlueTeam	RedTeam
Top	1	6
Jungle	2	7
Mid	3	8
BotCarry	4	9
Support	5	10

While nothing is preventing teammates from swapping team roles before a match or even during a match (e.g., a Top Laner picks Smite as a summoner spell or has the Unsealed Spellbook keystone rune and swaps their current summoner spell for Smite and becomes a de facto Jungler), it's safe to assume that the assignment of these team roles are cemented in place.

However, in the other Summoner's Rift game mode, Blind Pick, the selection of all ten champions are done and revealed simultaneously, and, therefore, team roles cannot be assumed to be in the same Participant ID order, nor can it be assumed that the five distinct team roles exist on each side as a match proceeds. For instance, one team may have two Junglers, while the other team has no Junglers.

Furthermore, while Riot Games appears to have a classification system in place for labeling a player in a certain lane and role, it has shown to be flawed, even in a game mode with an ordered champion selection as is the case in professional eSports matches. Below is a table representing the NA LCS 2018 Spring Split team roles. The column names are team roles that I programatically entered according to Participant ID, while the row names represent a concatentation of the `role` and `lane` variables that Riot Games assigned and were obtained from the data set:

```
library(dplyr)
nalcs_season_match_data <- read.csv(
  "../datasets/nalcs/nalcs_spring2018_match_player_stats.csv") %>%
  mutate(roleLane = paste(role, lane, sep = ", "))
table_roles <- table(nalcs_season_match_data$roleLane, nalcs_season_match_data$teamRole)
kable(table_roles, caption = "NA LCS Spring Split 2018 Team Role Assignments")
```

Table 2: NA LCS Spring Split 2018 Team Role Assignments

	BOTCARRY	JUNGLE	MID	SUPPORT	TOP
DUO, BOTTOM	77	0	57	77	0
DUO, MIDDLE	0	55	0	0	55
DUO_CARRY, BOTTOM	111	0	0	0	0
DUO_CARRY, MIDDLE	0	0	4	0	0
DUO_SUPPORT, BOTTOM	0	0	0	111	0
DUO_SUPPORT, MIDDLE	0	4	0	0	0
NONE, JUNGLE	9	173	58	8	57
SOLO, BOTTOM	5	0	0	38	0
SOLO, MIDDLE	0	2	115	0	0
SOLO, TOP	32	0	0	0	122

```
remove(nalcs_season_match_data)
```

Not only are there ten different combinations of Role and Lane variables in this data set, but there are a large number of manually-classified roles being auto-classified into different roles.

For instance, there are a significant number of Mid and Top Laners being assigned the `NONE, JUNGLE` `role-lane` combination. This can be theorized in one way: Riot Games has a classification system in place that assigns players to a `role-lane` according to where they are located on the map at a certain point in time in a match, particularly early.

The reason I make this theory is, because, since Junglers can play a pivotal role early in a match due to their ability to roam the map and "gank" (an amalgamation of "flank", "gang", and "kill") opposing Laners, a pre-laning phase tactic called counter-jungling, or invading the enemy Jungler, is used to hinder the enemy Jungler's ganking effectiveness during the laning phase. In this tactic, multiple teammates are often used in an attempt to ensure their team's Jungler early advantage, and therefore, when the time comes for the system to assign the `role-lane`, those non-Jungler teammates who are still in the jungle may inadvertantly be assigned the `NONE, JUNGLE` `role-lane` combination.

While the auto-classification system has shown to be flawed, at least it's safe to assume team roles for Draft Pick, Ranked, and eSports matches due to the structure cited in Figure 1, and many third-party League of Legends analytics websites, such as op.gg, champion.gg, and mobalytics.gg, appear to make that assumption. However, these sites miss out on analyzing data from Blind Pick matches, in which team role assumptions cannot be made. If the auto-classification system can be improved upon, then both Riot Games and these third-party websites can utilize this improved system for their future analytics.

Diving into the Data

The datasets we'll be using to answer this question was obtained and wrangled from the match data of the 2018 Spring Split seasons of four different professional Lol eSports leagues: the North Ameica LoL Championship Series (NALCS), the Europe LoL Championship Series (EULCS), LoL Champions Korea (LCK), and LoL Master Series (LMS), plus the 2018 Mid-Season Invitational (MSI), an international tournament similar to the UEFA Champions League in Football/Soccer. Specifically, for solving the problem, we'll use datasets that contain individual performance data of all players of each match of the eSports Leagues' season, and we'll also use those datasets to create per-game performance datasets.

Limitations

In the case of the NA LCS 2018 Spring Split, the season started using the Version 8.1 Patch of League of Legends, while the playoff finals series of the season used Version 8.5. Other LoL eSports leagues around the world used roughly the same range of patches for their 2018 Spring Split seasons, while the 2018 MSI used Version 8.8.

The reason I mention this, is because with every new patch Riot Games releases for LoL, the changes and tweaks to the game may possibly affect, to a significant degree, the metagame (or meta for short), which means the underlying strategies that can increase chances of success.

For instance, the 8.10 patch gave a significant increase of Experience Points for killing the Rift Scuttler, a non-hostile neutral minion that exists in The River (the diagonal opposite of the Mid Lane), which, in turn made selecting a Jungler champion that is strong at Level 2 for contesting the Scuttler, such as Graves or Xin Zhao, possibly more important.

Another significant meta-shifting patch was 8.11, which made marksman Botlane Carry champions, such as Ashe, Caitlyn, and Tristana, noticeably weaker both in damage output and durability. This has not only made marksman champions much less prevalent in the Botlane Carry role, but champions once previously thought to be suitable for only Top Laner or Mid Laner roles are starting to make their presence known as Botlane Carries in the 2018 Summer Split, such as Heimerdinger, Vladimir, and Swain.

Therefore, it's possible that any classification models created from and used for the 2018 Spring Split matches will not be as effective if used on 2018 Summer Split or Patch 8.11+ matches.

Obtaining and Cleaning/Wrangling the data:

In-depth details about how the data was obtained and wrangled can be found in this document: **DataWranglingReport.pdf**. Below, I will present the steps taken to reach the destination datasets used to solve the problem.

1. Discovering the API for obtaining match data

eSports matches were found in **lolesports.com**. While an individual match that has already concluded can easily be found by just clicking/tapping links alone, finding matches during the 2018 Spring Splits currently requires some manual hacking of the URL to reach them, such as **NA LCS 2018 Spring Split Week 1**.

From here, we can click away to find an individual match's details, such as **NA LCS 2018 Spring Split Week 1, Day 1, Team Liquid vs. TSM**. On this page, we can get find the API we need by opening the browser's Web Inspector, as shown in Figure 2.

2. Accumulating match IDs for the API

We can find the match IDs the same way we found the API. Figures 3 and 4 show the match ID strings we need to obtain match data for a particular match.

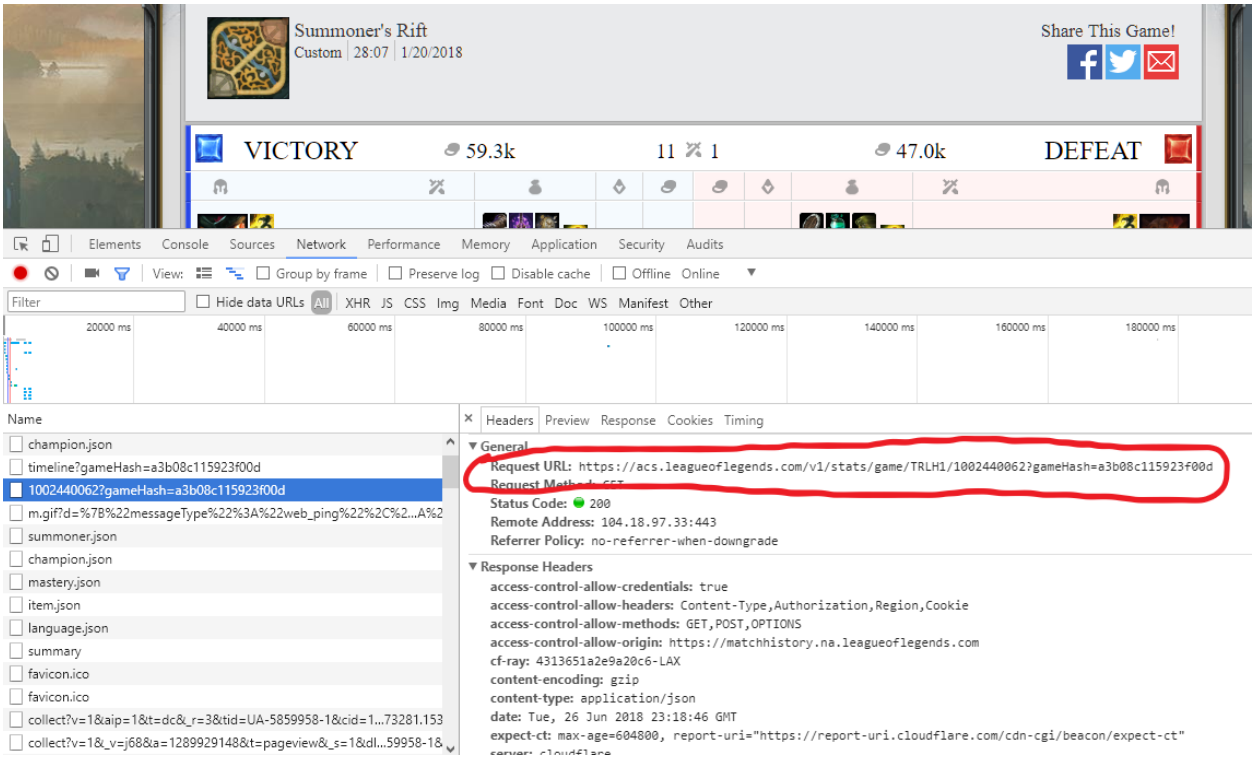


Figure 2: Web Inspector

Figure 3: Browser URL

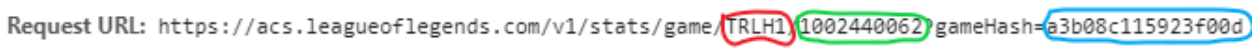


Figure 4: Web Inspector URL

Therefore, we can accumulate these match IDs by repeating step 1, and then copying and pasting the IDs into a CSV file, in which a portion of the NA LCS 2018 Spring Split is shown in table form in Figure 5.

```
library(knitr)
kable(head(read.csv("../gameid_data/NALCS_Spring2018.csv")), caption = "Match ID Data, First Six Matches
```

Table 3: Match ID Data, First Six Matches of NA LCS 2018 Spring Split

Region.ID	Game.ID	Hash.ID	Blue.Team	Red.Team	Tiebreaker	Playoff
TRLH1	1002440062	a3b08c115923f00d	Team Liquid	Team Solo Mid	FALSE	FALSE
TRLH1	1002440076	c426d3d50426edb3	100 Thieves	OpTic Gaming	FALSE	FALSE
TRLH1	1002440084	f0f86e52b6e472e9	Clutch Gaming	Golden Guardians	FALSE	FALSE
TRLH1	1002440095	fd3b9331ff5312e3	Echo Fox	FlyQuest	FALSE	FALSE
TRLH1	1002440106	d6441d4ec8f87534	Counter Logic Gaming	Cloud9	FALSE	FALSE
TRLH1	1002440127	361bcc2e848641d2	OpTic Gaming	Team Liquid	FALSE	FALSE

3. Obtaining Match Data for an Entire Season

Below is the R script/code used to obtain the top-level match data for a few matches of the NA LCS 2018 Spring Split season.

```
library(httr)
library(dplyr)
library(tidyr)
library(jsonlite)

acs_prefix_domain <- "https://acs.leagueoflegends.com"

# API call helper from response
process_uri <- function(str_uri) {
  #print(str_uri)
  response <- GET(str_uri)
  #print(response$status_code)
  while (response$status_code != 200) {
    Sys.sleep(2)
    response <- GET(str_uri)
  }
  json <- jsonlite::fromJSON(content(response, as = "text"))
  return(json)
}
```

```r
# URI building helper function
get_acs_match_by_matchid <- function(chr_platform_id,
                                     num_match_id,
                                     chr_game_hash = "") {
  uri <- paste(acs_prefix_domain,
               "/v1/stats/game/",
               chr_platform_id,
               "/", num_match_id,
               ifelse(chr_game_hash != "", paste(
                 "?gameHash=", chr_game_hash, sep = ""), ""),
               sep = "")
  return(process_uri(uri))
}

# Iterate through match IDs data frame
get_league_match_data_list <- function(league_matchid_df) {
  matchlist <- list()
  for (i in 1:nrow(league_matchid_df)) {
    matchlist[[i]] <- get_acs_match_by_matchid(
      league_matchid_df$Region.ID[[i]], league_matchid_df$Game.ID[[i]],
      chr_game_hash = league_matchid_df$Hash.ID[[i]])
  }

  return(matchlist)
}

# Getting portion of NA LCS Spring Split matches data
nalcs_matches <- get_league_match_data_list(
  head(read.csv("../gameid_data/NALCS_Spring2018.csv")))
str(nalcs_matches, max.level = 1)
```

```
## List of 6
##  $ :List of 13
##  $ :List of 13
##  $ :List of 13
##  $ :List of 13
##  $ :List of 13
##  $ :List of 13
```

We see that we are getting a list of match data.

Below, we see some details about a single match:

```
str(nalcs_matches[[1]], max.level = 2)
```

```
## List of 13
##  $ gameId               : int 1002440062
##  $ platformId           : chr "TRLH1"
##  $ gameCreation         : num 1.52e+12
##  $ gameDuration         : int 1687
##  $ queueId              : int 0
##  $ mapId                : int 11
##  $ seasonId             : int 11
##  $ gameVersion          : chr "8.1.213.4336"
##  $ gameMode             : chr "CLASSIC"
##  $ gameType             : chr "CUSTOM_GAME"
##  $ teams                :'data.frame':   2 obs. of  16 variables:
##   ..$ teamId             : int [1:2] 100 200
##   ..$ win                : chr [1:2] "Win" "Fail"
##   ..$ firstBlood         : logi [1:2] TRUE FALSE
##   ..$ firstTower         : logi [1:2] TRUE FALSE
##   ..$ firstInhibitor     : logi [1:2] TRUE FALSE
##   ..$ firstBaron         : logi [1:2] TRUE FALSE
##   ..$ firstDragon        : logi [1:2] FALSE TRUE
##   ..$ firstRiftHerald    : logi [1:2] TRUE FALSE
##   ..$ towerKills         : int [1:2] 10 2
##   ..$ inhibitorKills     : int [1:2] 1 0
##   ..$ baronKills         : int [1:2] 1 0
##   ..$ dragonKills        : int [1:2] 2 2
##   ..$ vilemawKills       : int [1:2] 0 0
##   ..$ riftHeraldKills    : int [1:2] 1 0
##   ..$ dominionVictoryScore: int [1:2] 0 0
##   ..$ bans               :List of 2
##  $ participants         :'data.frame':   10 obs. of  8 variables:
##   ..$ participantId           : int [1:10] 1 2 3 4 5 6 7 8 9 10
##   ..$ teamId                  : int [1:10] 100 100 100 100 100 200 200 200 200 200
##   ..$ championId              : int [1:10] 41 79 90 18 44 150 102 13 429 12
##   ..$ spell1Id                : int [1:10] 4 11 4 4 3 4 11 4 4 4
##   ..$ spell2Id                : int [1:10] 12 4 7 7 4 12 4 7 7 14
##   ..$ highestAchievedSeasonTier: chr [1:10] "UNRANKED" "UNRANKED" "UNRANKED" "UNRANKED" ...
##   ..$ stats                   :'data.frame':    10 obs. of  101 variables:
##   ..$ timeline                :'data.frame':    10 obs. of  10 variables:
##  $ participantIdentities:'data.frame':   10 obs. of  2 variables:
##   ..$ participantId: int [1:10] 1 2 3 4 5 6 7 8 9 10
##   ..$ player       :'data.frame':    10 obs. of  2 variables:
```

4. Wrangling and cleaning match data into desired datasets.

Here, we will iterate through each individual set of match data, clean it up so that we can get ten observations (representing the ten players in a match), and then concatenate those ten observations into an accumulative dataset.

```r
#### Creating data frame of champion names linked to their champion IDs.
ddragon_prefix_domain <- "https://ddragon.leagueoflegends.com"
get_champion_data_by_version <- function(chr_version_number = "8.8.2") {
  uri <- paste(ddragon_prefix_domain, "/cdn/",
               chr_version_number, "/data/en_US/champion.json", sep = "")
  return(process_uri(uri))
}
# Champion data
champions_list <- get_champion_data_by_version()$data
champions_df <- data.frame(NULL)
for (i in 1:length(champions_list)) {
  champions_df <- champions_df %>% bind_rows(data.frame(champions_list[[i]]))
}
champions_df_simple <- champions_df %>%
  select(name, key) %>%
  distinct() %>%
  rename(championId = key) %>%
  mutate(championId = as.numeric(championId))
remove(champions_list)
remove(champions_df)

#@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
# Concatenates the "participants" DFs of each match together
# combine_teammate_stats determines whether we want to combine the stats of the teammates
# into total numbers
get_accum_matches_participants <- function(league_matchlist, league_matchid_df,
                                           combine_teammate_stats = FALSE) {
  league_matches_participants_accum <- data.frame(NULL)

  for (i in 1:length(league_matchlist)) {
    flattened_df <- get_flattened_match_participants_df(
      league_matchlist[[i]]$participants,
      league_matchlist[[i]]$participantIdentities)
    flattened_df["gameNumber"] <- rep(i, 10)
    flattened_df["isTiebreaker"] <- rep(league_matchid_df[i,]$Tiebreaker, 10)
    flattened_df["isPlayoff"] <- rep(league_matchid_df[i,]$Playoff, 10)
    flattened_df["duration"] <- rep(league_matchlist[[i]]$gameDuration, 10)
    tmp_fdf1 <- flattened_df %>% filter(teamId == "Blue")
    tmp_fdf1["teamName"] <- unname(unlist(c(league_matchid_df[i, rep("Blue.Team", 5)])))
    tmp_fdf2 <- flattened_df %>% filter(teamId == "Red")
    tmp_fdf2["teamName"] <- unname(unlist(c(league_matchid_df[i, rep("Red.Team", 5)])))

    flattened_df <- bind_rows(tmp_fdf1, tmp_fdf2)

    flattened_df['teamRole'] <- NULL
    # Get team roles
    for (j in 1:nrow(flattened_df)) {
      if (flattened_df[j, 'participantId'] == 1 ||
          flattened_df[j, 'participantId'] == 6) {
```

```r
        flattened_df[j, 'teamRole'] = "TOP"
      } else if (flattened_df[j, 'participantId'] == 2 ||
                 flattened_df[j, 'participantId'] == 7) {
        flattened_df[j, 'teamRole'] = "JUNGLE"
      } else if (flattened_df[j, 'participantId'] == 3 ||
                 flattened_df[j, 'participantId'] == 8) {
        flattened_df[j, 'teamRole'] = "MID"
      } else if (flattened_df[j, 'participantId'] == 4 ||
                 flattened_df[j, 'participantId'] == 9) {
        flattened_df[j, 'teamRole'] = "BOTCARRY"
      } else {
        flattened_df[j, 'teamRole'] = "SUPPORT"
      }
    }

    league_matches_participants_accum <- league_matches_participants_accum %>%
      bind_rows(flattened_df)
  }

  return(league_matches_participants_accum)
}

#@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
get_flattened_match_participants_df <- function(match_participants_df, match_participantids_df) {
  # uses jsonlite flatten() function
  ret_df <- match_participants_df %>%
    select(-stats, - timeline) %>%
    bind_cols(match_participantids_df$player) %>%
    inner_join(champions_df_simple) %>%
    inner_join(match_participants_df$stats) %>%
    inner_join(match_participants_df$timeline %>%
                 flatten())
  # Change teamId = 100/200 to Blue/Red, replace NA's in the Deltas with 0s
  ret_df <- ret_df %>%
    mutate(teamId = replace(teamId, grepl('100', teamId), 'Blue')) %>%
    mutate(teamId = replace(teamId, grepl('200', teamId), 'Red'))

  return(ret_df)
}
```

```r
# Note: just the first six matches
nalcs_season_match_player_data <- get_accum_matches_participants(
  nalcs_matches, head(read.csv("../gameid_data/NALCS_Spring2018.csv")))
kable(nalcs_season_match_player_data[1:20,] %>%
        select(participantId, summonerName, win, kills,
               deaths, assists, teamRole, role, lane),
      caption = "Sample of Match-By-Match Player Data")
```

Table 4: Sample of Match-By-Match Player Data

participantId	summonerName	win	kills	deaths	assists	teamRole	role	lane
1	TL Impact	TRUE	3	0	6	TOP	SOLO	TOP
2	TL Xmithie	TRUE	0	0	9	JUNGLE	NONE	JUNGLE
3	TL Pobelter	TRUE	2	1	7	MID	SOLO	MIDDLE

participantId	summonerName	win	kills	deaths	assists	teamRole	role	lane
4	TL Doublelift	TRUE	5	0	5	BOTCARRY	DUO_CARRY	BOTTOM
5	TL Olleh	TRUE	1	0	9	SUPPORT	DUO_SUPPORT	BOTTOM
6	TSM Hauntzer	FALSE	0	3	0	TOP	SOLO	TOP
7	TSM MikeYeung	FALSE	0	3	1	JUNGLE	NONE	JUNGLE
8	TSM Bjergsen	FALSE	1	0	0	MID	SOLO	MIDDLE
9	TSM Zven	FALSE	0	2	0	BOTCARRY	DUO_CARRY	BOTTOM
10	TSM Mithy	FALSE	0	3	1	SUPPORT	DUO_SUPPORT	BOTTOM
1	100 Ssumday	TRUE	1	3	5	TOP	SOLO	TOP
2	100 Meteos	TRUE	1	2	6	JUNGLE	NONE	JUNGLE
3	100 Ryu	TRUE	1	0	5	MID	SOLO	MIDDLE
4	100 Cody Sun	TRUE	6	1	3	BOTCARRY	DUO	BOTTOM
5	100 aphromoo	TRUE	0	1	8	SUPPORT	DUO	BOTTOM
6	OPT zig	FALSE	1	3	4	TOP	SOLO	TOP
7	OPT Akaadian	FALSE	0	2	5	JUNGLE	NONE	JUNGLE
8	OPT PowerOfEvil	FALSE	4	0	2	MID	SOLO	MIDDLE
9	OPT Arrow	FALSE	1	1	4	BOTCARRY	DUO_CARRY	BOTTOM
10	OPT LemonNation	FALSE	1	3	2	SUPPORT	DUO_SUPPORT	BOTTOM

Table 4 shows just a portion of the data set we'll be using to solve this problem. Additionally, we'll use this dataset to create the per-game performance dataset, as presented in the code below.

```
# Gets individual per-game average performace data
get_league_season_summoner_avgs <- function(league_matches_player_stats) {
  league_season_participants_accum <- league_matches_player_stats

  # Create avg stats DF groups by lane and role
  league_season_participants_accum <-
  (league_season_participants_accum %>%
  group_by(teamName, summonerName, teamRole) %>%
  summarize_at(vars(duration, kills:assists, totalDamageDealt:trueDamageDealt,
                    totalDamageDealtToChampions:firstBloodKill,
                    firstTowerKill:firstInhibitorAssist, 'creepsPerMinDeltas.10.20',
                    'creepsPerMinDeltas.0.10', 'xpPerMinDeltas.10.20',
                    'xpPerMinDeltas.0.10', 'goldPerMinDeltas.10.20',
                    'goldPerMinDeltas.0.10', 'damageTakenPerMinDeltas.10.20',
                    'damageTakenPerMinDeltas.0.10'), mean)) %>%
  # Tallying wins and losses by summoner name
  inner_join(league_season_participants_accum %>%
    group_by(teamName, summonerName, teamRole, win) %>%
    tally() %>%
    spread(win, n) %>% # "transposes" the DF so that TRUE (win) and FALSE (loss) are the column names
    rename('losses' = 'FALSE', 'wins' = 'TRUE') %>% # renames the T/F columns to W/L
    mutate_at(vars(wins, losses), funs(replace(., is.na(.), 0))))

  # Adding KDA Ratio column
  league_season_participants_accum <- league_season_participants_accum %>%
    mutate(KDA = (kills + assists) / deaths)

  # Reordering columns - teamName, wins, losses, <everything else>
  league_season_participants_accum <- league_season_participants_accum[
    , c(1, 2, 55, 54, 3:7, 56, 8:53)]
}
```

```
nalcs_matches_player_stats <- read.csv(
  "../datasets/nalcs/nalcs_spring2018_match_player_stats.csv")
nalcs_season_player_avgs <- get_league_season_summoner_avgs(nalcs_matches_player_stats)
kable(nalcs_season_player_avgs[1:20, 2:10], caption =
        "Sample of Per Game Player Averages, NA LCS 2018 Spring Split")
```

Table 5: Sample of Per Game Player Averages, NA LCS 2018 Spring Split

summonerName	wins	losses	teamRole	duration	kills	deaths	assists	KDA
100 aphromoo	16	11	SUPPORT	2308.481	0.3703704	2.148148	6.222222	3.068966
100 Cody Sun	16	11	BOTCARRY	2308.481	3.7407407	1.222222	4.000000	6.333333
100 Meteos	16	11	JUNGLE	2308.481	1.4814815	1.888889	5.333333	3.607843
100 Ryu	16	11	MID	2308.481	1.9629630	1.703704	4.407407	3.739130
100 Ssumday	16	11	TOP	2308.481	1.8148148	1.703704	4.407407	3.652174
C9 Jensen	12	11	MID	2230.957	3.2173913	1.130435	4.826087	7.115385
C9 Licorice	12	11	TOP	2230.957	2.5652174	2.391304	4.043478	2.763636
C9 Smoothie	12	11	SUPPORT	2230.957	0.6521739	2.478261	7.260870	3.192982
C9 Sneaky	12	11	BOTCARRY	2230.957	2.7391304	1.695652	4.913043	4.512821
C9 Svenskeren	12	11	JUNGLE	2230.957	1.4782609	2.695652	6.478261	2.951613
CG Apollo	16	16	BOTCARRY	2200.188	2.2500000	1.468750	4.187500	4.382979
CG Febiven	16	16	MID	2200.188	2.8437500	1.125000	3.625000	5.750000
CG Hakuho	16	16	SUPPORT	2200.188	0.6250000	1.781250	5.718750	3.561403
CG LirA	16	16	JUNGLE	2200.188	1.5000000	1.843750	4.531250	3.271186
CG Solo	16	16	TOP	2200.188	1.3750000	2.000000	3.718750	2.546875
CLG Biofrost	7	11	SUPPORT	2292.556	0.5000000	2.500000	7.666667	3.266667
CLG Darshan	7	11	TOP	2292.556	2.0555556	2.333333	4.888889	2.976190
CLG huhi	7	11	MID	2292.556	2.8333333	2.333333	5.444444	3.547619
CLG Reignover	7	11	JUNGLE	2292.556	1.0000000	2.388889	6.666667	3.209302
CLG Stixxay	7	11	BOTCARRY	2292.556	4.0555556	2.222222	3.666667	3.475000

Exploratory Analysis

For additional details on the exploratory analysis of the datasets see this document: **ExploratoryAnalysis-Report.pdf**. Below, we'll look at the features/variables that stood out in my findings for distinguishing team roles, as well as plots that show these distinguishing features.

First, here are the variables that will be shown in the plots:

variableName	description
kills	The number of enemy champions killed.
assists	The number of enemy champions assisted in killing.
magicDamageDealt	The amount of magic damage dealt.
physicalDamageDealt	The amount of physical damage dealt.
magicDamageDealtToChampions	The amount of magic damage dealt to enemy champions only.
physicalDamageDealtToChampions	The amount of physical damage dealt to enemy champions only.
totalHeal	The amount of health points the player has regained.
totalUnitsHealed	The number of entities a player healed.
damageSelfMitigated	The amount of health points that were not lost from damage.
totalDamageTaken	The amount of damage a player took from various sources.
neutralMinionsKilled	The number of neutral monsters killed by a player.
timeCCingOthers	The weighted sum of all CC applied
totalTimeCrowdControlDealt	The sum of all CC applied
champLevel	The (experience) level of a player at the end of a match.
visionWardsBoughtInGame	The number of wards (i.e. surveillance items) a player purchased.
wardsPlaced	The number of wards a player placed in the arena.
wardsKilled	The number of enemy wards a player destroyed.

The primary reason we're using these variables is because, as I was sorting this dataset by variables, I noticed how certain roles were at the top of some variables, while certain roles were always at the bottom for others.

We'll be using the NALCS 2018 Spring Split per-game player averages dataset for creating these plots.

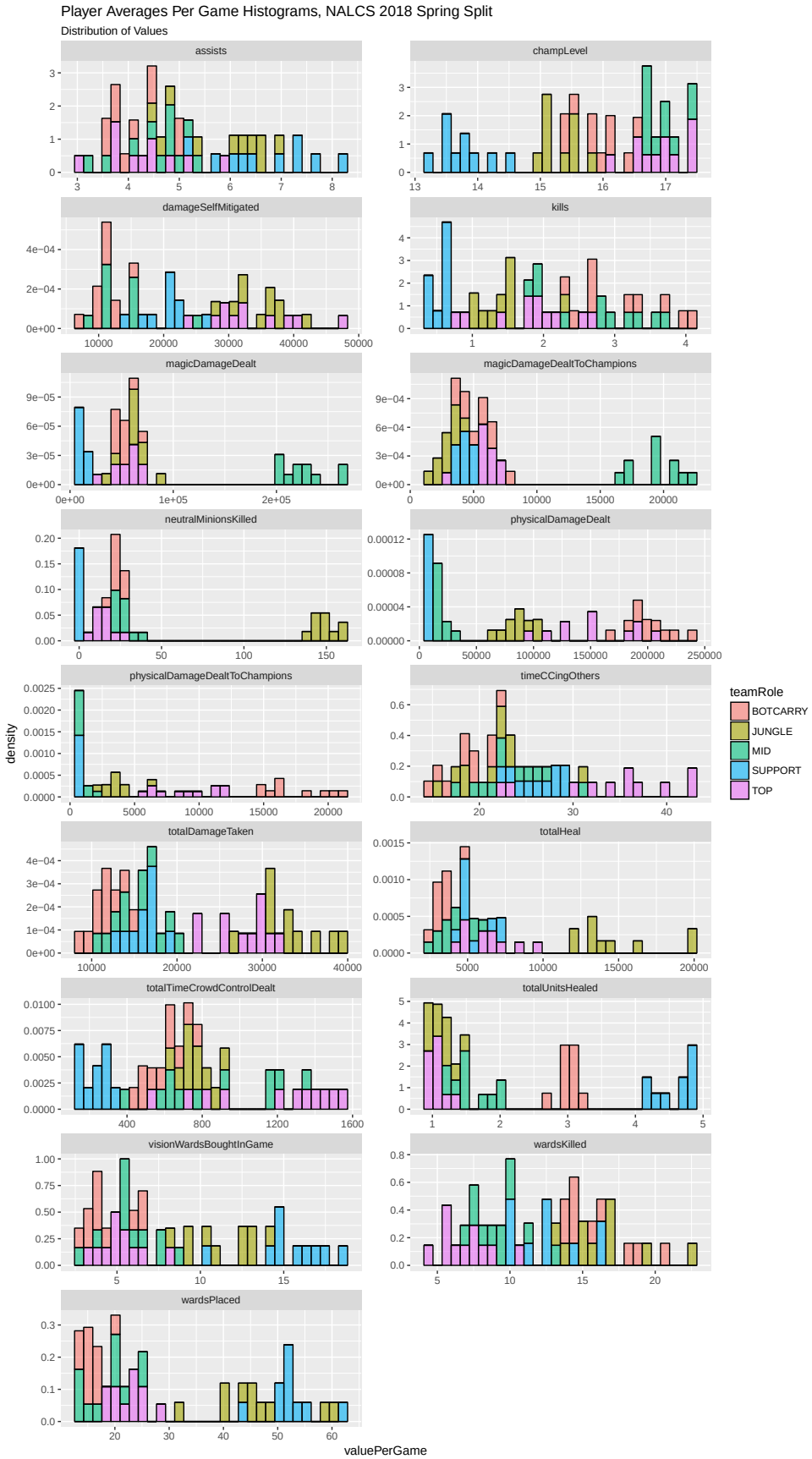
```
library(dplyr)
library(tidyr)
library(ggplot2)
# Preparation for next nine plots.
nalcs_matches_player_avgs <- read.csv("../datasets/nalcs/nalcs_spring2018_season_summoner_avgs.csv")
nalcs_plot_player_avgs <- nalcs_matches_player_avgs %>%
  filter(wins + losses >= 6) %>%
  ggplot()
```

Here are the plots used for this exploratory analysis.

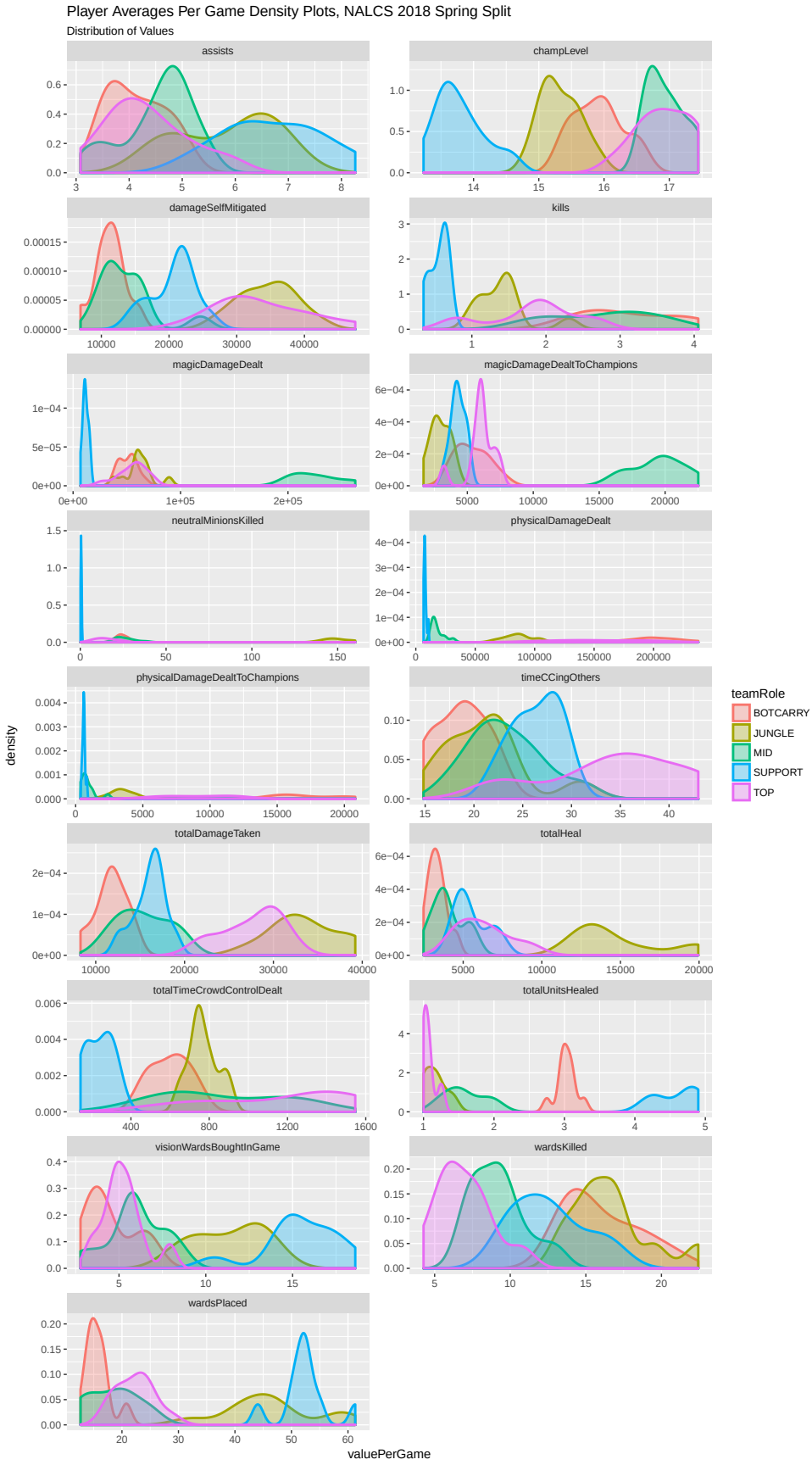
```
#### Facet-wrapped plots
nalcs_season_summoner_avgs_gathered <- nalcs_matches_player_avgs %>%
  gather(kills, assists, magicDamageDealt, physicalDamageDealt, magicDamageDealtToChampions,
         physicalDamageDealtToChampions, totalHeal, totalUnitsHealed, damageSelfMitigated,
         totalDamageTaken, neutralMinionsKilled, timeCCingOthers, totalTimeCrowdControlDealt,
         champLevel, visionWardsBoughtInGame, wardsPlaced, wardsKilled, key = "varName",
         value = "valuePerGame")

# Template for next three plots
nalcs_plot_player_avgs_gathered <- nalcs_season_summoner_avgs_gathered %>%
  filter(wins + losses >= 6) %>%
  ggplot()
```

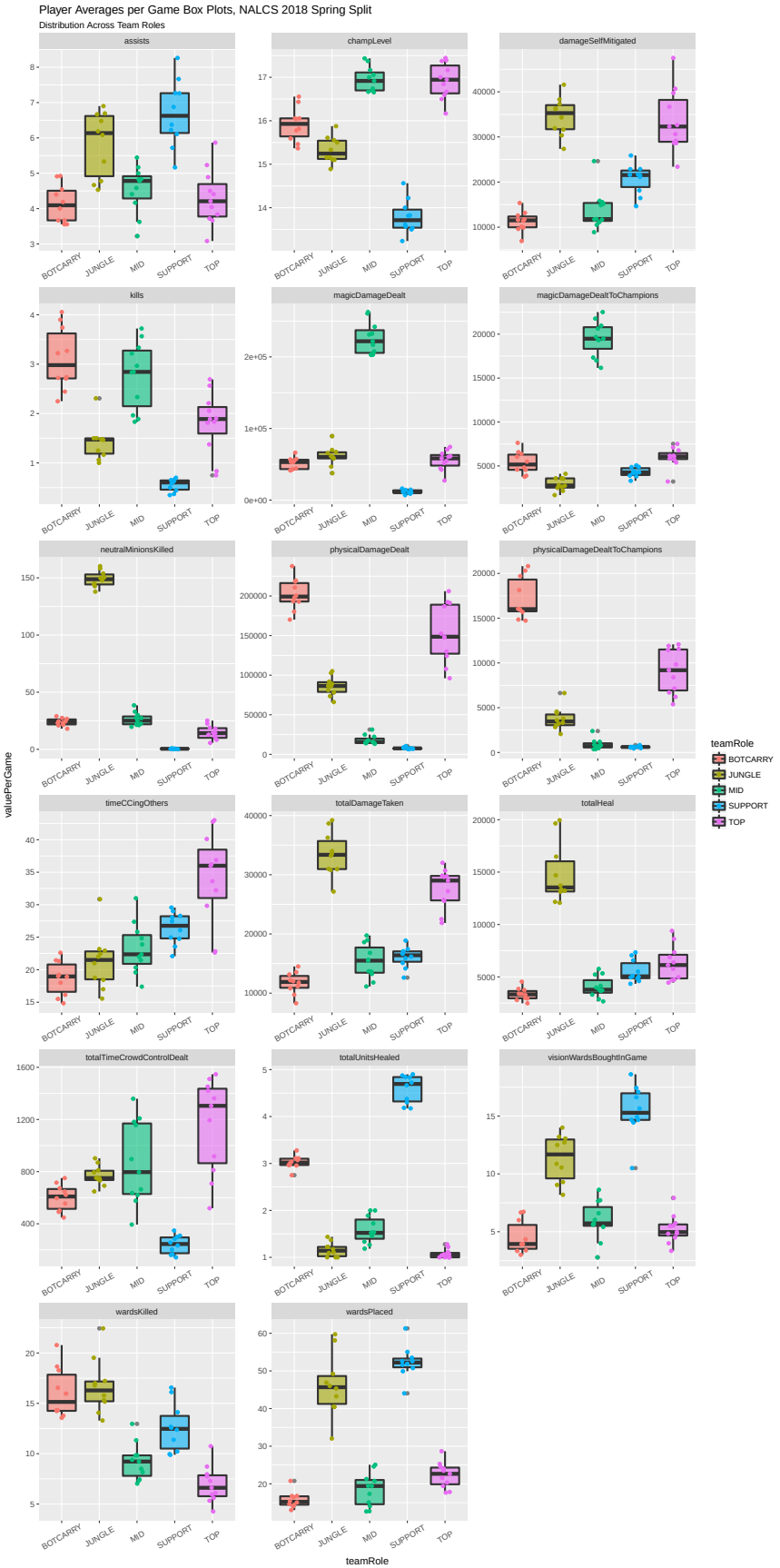
```r
# Histograms
nalcs_plot_player_avgs_gathered +
  geom_histogram(mapping = aes(x = valuePerGame, y = ..density.., fill = teamRole),
                 color = "black", alpha = .6) +
  facet_wrap(~varName, scales = "free", ncol = 2) +
  labs(
    title = "Player Averages Per Game Histograms, NALCS 2018 Spring Split",
    subtitle = "Distribution of Values")
```


Player Averages Per Game Histograms, NALCS 2018 Spring Split
Distribution of Values
assists
champLevel
damageSelfMitigated
kills
magicDamageDealt
magicDamageDealtToChampions
neutralMinionsKilled
physicalDamageDealt
physicalDamageDealtToChampions
timeCCingOthers
totalDamageTaken
totalHeal
totalTimeCrowdControlDealt
totalUnitsHealed
visionWardsBoughtInGame
wardsKilled
wardsPlaced
density
valuePerGame
teamRole
BOTCARRY
JUNGLE
MID
SUPPORT
TOP

```
nalcs_plot_player_avgs_gathered +
  geom_density(mapping = aes(x = valuePerGame, color = teamRole, fill = teamRole),
               alpha = .3, size = 1) +
  facet_wrap(~varName, scales = "free", ncol = 2) +
  labs(
    title = "Player Averages Per Game Density Plots, NALCS 2018 Spring Split",
    subtitle = "Distribution of Values")
```


Player Averages Per Game Density Plots, NALCS 2018 Spring Split
Distribution of Values
assists
champLevel
damageSelfMitigated
kills
magicDamageDealt
magicDamageDealtToChampions
neutralMinionsKilled
physicalDamageDealt
physicalDamageDealtToChampions
timeCCingOthers
totalDamageTaken
totalHeal
totalTimeCrowdControlDealt
totalUnitsHealed
visionWardsBoughtInGame
wardsKilled
wardsPlaced
density
valuePerGame
teamRole
BOTCARRY
JUNGLE
MID
SUPPORT
TOP

```r
# Box Plots
nalcs_plot_player_avgs_gathered +
  geom_boxplot(mapping = aes(x = teamRole, y = valuePerGame, fill = teamRole),
               size = 1.00, alpha = .6) +
  geom_jitter(width = 0.15, mapping = aes(x = teamRole, y = valuePerGame, color = teamRole)) +
  facet_wrap(~ varName, scales = "free", ncol = 3) +
  theme(axis.text.x = element_text(angle=30, vjust=0.6)) +
  labs(
    title = "Player Averages per Game Box Plots, NALCS 2018 Spring Split",
    subtitle = "Distribution Across Team Roles")
```


Player Averages per Game Box Plots, NALCS 2018 Spring Split
Distribution Across Team Roles
assists
champLevel
damageSelfMitigated
kills
magicDamageDealt
magicDamageDealtToChampions
neutralMinionsKilled
physicalDamageDealt
physicalDamageDealtToChampions
timeCCingOthers
totalDamageTaken
totalHeal
totalTimeCrowdControlDealt
totalUnitsHealed
visionWardsBoughtInGame
wardsKilled
wardsPlaced
BOTCARRY
JUNGLE
MID
SUPPORT
TOP
valuePerGame
teamRole

Here are some details and explanations of how and why the plots and data resulted as they did.

kills: It's pretty clear in all three plots that Supports achieve the least number of kills per game, followed by Junglers and Top Laners, while Mid Laners and Bottom Lane Carries are mixed together at the top. The main explanations for Supports are that the champions representing them are typically inherently the weakest in terms of overall damage output, and that they play an auxiliary role in protecting their teammates in various ways.

assists: We see nearly the opposite of ***kills***. Supports followed by Junglers average the most assists in a game. Supports typically, though lacking in damage output, provide the most protection, CC, buffs, and/or debuffs, while Junglers provide ganks for their teammates since they roam throgh most of the map.

physical damage dealt/dealt to champions: The champions selected by Botlane Carries are almost always ranged physical damage dealers aka marksmen. Later in a match these Botlane Carries are capable of dealing high amounts of damage per second (dps) while typcially avoiding taking damage themselves, which make them less likely to be killed and, thus, be in fights longer to be able to deal such damage.
Champions selected by Top Laners and Junglers are usually melee (close range) physical damage dealers, which make them more likely battle on the front lines of team fights, though Junglers usually use hit-and-run tactics like assassins, while Top Laners stay in the front line in a fight and also combat enemy Top Laners on top of enemy minions during the Laning Phase, which is why they deal more Physical Damage than do Junglers.

magic damage dealt/dealt to champions: The champions selected by Mid Laners are almost always inherently magic dealers or mages. There are also some champions selected by Supports that can be played in Midlane roles in separate matches (such as Karma and Morgana), but as Supports, those champions' main jobs for those players are not to damage enemies.

neutral minions killed: Since all the neutral minions are only located in the jungle, it's obvious that Junglers would kill the most neutral minions, while the other roles only kill jungle monsters later in the match.

total damage taken: While in-lane champions do combat their enemy counterparts and enemy minions during the laning phase, they also fight conservatively, because their main purpose in this phase is to accumulate gold and experience points (XP) by killing enemy minions, while their secondary purpose is to hinder their opponents' abilities of doing those things. Junglers, on the other hand, are almost always by themselves when they are killing the jungle monsters (i.e., neutral minions), which means they are also taking damage from these monsters, which explains why Junglers are usually at the top of the **totalDamageTaken** category.

total heal: There are two primary reasons why Junglers have the highest total heal. 1. They almost always pick the summoner spell Smite, which is used to deal a large chunk of damage to monsters while also healing the caster of the spell. 2. Only champions who have Smite are capable of purchasing items (e.g., Hunter's Machete, Hunter's Talisman, Skirmisher's Sabre, and Stalker's Blade) that provide a significant amount of life steal (i.e., healing the attacker while dealing damage) against monsters. Therefore, those equipped with these items will always heal themselves a lot, as long as they're attacking monsters.

total units healed: While Junglers are typically capable of healing themselves, they are usually not able to heal their teammates, in which many champions suitable for the Support role are. However, even if they are not (such as Braum, Morgana, Pyke, and Thresh), they may eventually purchase items that are capable of healing teammates, such as Redemption. While it's true that any player can purchase Redemption, it's considered a suboptimal strategy if a non-Support player does so.

time CCing others and ***total time crowd control dealt***: A large number of champions that are selected for the Top Laner role have abilities that deal crowd control, which is essentially the hindrance of an opponent's mobility, while the most popular Top Lane champions in eSports are those which can deal crowd control to multiple enemy champions in an area, such as Cho'Gath, Ornn, Sion, and Swain. The plots also show Mid Laners and Supports are capable of dealing crowd control, though those champions playing those roles ususually lack the durability and/or sustainability that is a key trait for a Top Laner.

vision wards bought in game and ***wards placed***: The plots show that Junglers and Supports both purchase and place the most wards, i.e., surveillance items. Since subterfuge is usually one of the main functions of Junglers (because they roam around so much of the map), it is important that while they try to gank enemy champions, they do not get counter-ganked or counter-jungled in return, so it's natural that they purchase and place wards to protect both themselves and their teammates.
For Supports, because their main role is to provide auxiliary support, and because the enhancement items they typically purchase are usually less expensive than the items that players of other roles purchase, they have more "disposable income" to spend on and place wards.

wards killed: The plots show that Junglers and Botlane Carries destroy the most wards. For Junglers, since they usually place wards in the jungle, it's almost natural that they would encounter wards placed by their enemies, as well, though enemy Control Wards can only be destroyed if they are revealed by a nearby allied Control Ward or an Oracle Lens. To explain why Botlane Carries destroy about an equal amount of wards, one can observe from watching a LoL match that Botlane Carries and Supports are "attached at the hip". Though champions selected for Botlane Carry roles are usually capable dealing the most amount of sustained damage over a period of time, they are also considered the most fragile, and, thus, need a Support by their side in order to stay alive. Therefore, since Supports place the most wards, since Botlane Carries and Supports stick together, and since Botlane Carries are the most efficient damage dealers, if a Support spots an enemy ward and their Botlane Carry partner is nearby, then it's more time efficient for the Botlane Carry to destroy the enemy ward.

Exploratory Analysis Conclusion

With such distinguishable features, it may be possible to classify players and/or champions based on their performance data. Top Laners get the least assists, do the least healing of others, and deal the most crowd control time. Junglers heal themselves the most, take and self-mitigate the most total damage, kill the most neutral minions, and buy, purchase, and kill the second-most wards. Mid Laners deal the most magic damage overall and to champions and have one of highest finishing champ levels. Bottom Lane Carrie deal the most physical damage overall and to champions, are healed the least, take least damage, and kill the most wards. Finally, Supports get the least kills but the most assists, deal the least amount of magic and physical damage overall, heal the most units, have the lowest finishing champ levels, and buy and place the most wards.