LCS 2017 Summer Split Experimental Analysis

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1 Introduction: Problem Description

The dataset **LCS 2017 Summer Split Fantasy Player & Team Stats** contains per-player and per-team information for different League of Legends games during a tournament called the LCS 2017 Summer Split. It is composed of two data tables.

- **LCS Team Stats Summer Split 2017**: Contains per-team data with each row representing one team vs one opponent for as many games as they played against each other
- **LCS Players Stats Summer Split 2017**: Contains per-player data with each row representing the players performance against a particular team for as many games as they played against each other

We seek to understand the effects of in-game features on the **total points** a team receives in a game as well as determine the roles that contribute the most to the **total points** per team and across each team.

2 Experimental Analysis

2.1 Dataset Design

As stated in the introduction this dataset is split between two files, a per-team dataset and a per-player dataset. Both of these datasets are heavily unbalanced.
The per-team dataset contains the following features:

- Team: Either the name of the team or the team abbreviation specifying who the team played against for that row.
- Results: The win-loss record for that team against another team.
- Total Points: The total points, cumulative across each game or per team vs team. This is our main response variable.
- Average Points per Game: An average number of points per game. This is strongly correlated with the total points column, so we omitted this from the analysis.

- Games Played: The number of games played by that team against another team.
- Wins: Total number of wins for that team or the specific best-of-three series containing the team. Teams receive 2 points per win.
- Losses: Total number of losses for that team or the specific best-of-three series containing the team.
- First Bloods: The number of times the team scored the first player kill in a game vs another team. Teams receive 2 points per first blood earned.
- Dragon Kills: The number of dragons killed across all games vs the opposing team. Teams receive 1 point per dragon killed.
- Baron Kills: The number of Barons killed across all games vs the opposing team. Teams receive 1 points per Baron killed.
- Towers Destroyed: The number of towers destroyed across all games vs the opposing team. Teams receive 1 point per tower destroyed.
- 30-min win: The number of times a team won the game in less than 30-minutes against a particular team. Teams receive 2 points if they win in less than 30 minutes.

The per-player dataset contains the following features:

- Name: The name of the player.
- Role: The role of the player.
- Team: Either the name of the team or the specific best-of-three series containing the team.
- Results: The win-loss record for that player against an opponent.
- Total Points: The total points, cumulative across games or per-opponent, each player received. This is our main response variable.
- Average Points: The average number of points scored by that player across all games or per-opponent. This is strongly correlated with the total points column, so we omitted this from the analysis.
- Games Played: The number of games played by that player in total or against each team.
- Kills: The number of kills the player achieved, cumulative or against each team. Players receive 2 points per kill.
- Deaths: The number of times the player was killed, cumulative or against each team. Players lose 0.5 points per death.

- Assists: The number of assists the player achieved, cumulative or against each team. Players receive 1.5 points per assist.

- Creep Kills: The number of minions and jungle monsters, specifically those with low HP (health points) killed by the player, cumulative and against each team. Players receive 0.001 points per creep kill.

- Triple_Quadra_Penta: The number of triple, quadra, and penta kills scored by the player, cumulative and against each team. Players receive 2 points for a triple kill, 5 points for a quadra kill, and 10 points for a penta kill.

Breakdown of League of Legends roles:

- AD Carry: During the early stages of the game, this role is responsible for doing a lot of damage in order to kill the opponent team's AD Carry, and eventually, kill the opponent's team. They have low health and must rely on the assistance of another teammate.

- Mid: This role, like the ADC, is responsible for causing significant damage. They do not, however, require the assistance of another player and can play on their own. Their position in the middle lane gives them the freedom to roam and assist their teammates.

- Support: This role is in responsible for protecting, sustaining, and supporting the ADC. They initiate team fights since they have several crowd control effects in their arsenal.

- Jungler: This role is responsible for controlling the jungle, which is the area of the map between the three lanes. They also assist teammates by roaming the map and causing fights to be uneven in order to acquire a strategic edge.

- Top: This role is in charge of being the tank, or a player who can take a lot of damage before being killed. They become the focal point of team engagements, attempting to attack or stun high priority enemies.

There were a number of players who played 0 games, most likely backup players, so these players were removed from the dataset.

Many of these features are continuous variables, so we transformed them into factors by grouping certain ranges into Low, Medium, and High categories:

Team Categories:

Feature	Low	Medium	High
Towers Destroyed	0-10	11-20	21+
Dragons Killed	0-3	4-7	8+
Barons Killed	0-1	2-3	4+

Player Categories:

Feature	Low	Medium	High
Kills	0-5	6-10	11+
Deaths	0-5	6-10	11+
Assists	0-10	11-20	21+
Creep Kills	0-400	401-800	801+

3 Statistical Analysis

In this section we describe a number of the questions we hope to answer in this dataset.

3.1 Per Player Role Analysis

For this question, we want to determine if the role of a player significantly influences the total number of points a player receives. Also, we want to determine if there are significant differences in how each role contributes to the total points a player receives.

We consider a one-way layout model:

$$y_{ij} = \mu + \tau_i + \epsilon_{ij}$$

where μ is the overall mean and τ_i is the role effect.

```
              Df Sum Sq Mean Sq F value   Pr(>F)
Roles          4    129   32.27   10.79 1.26e-08 ***
Residuals   1491   4457    2.99
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

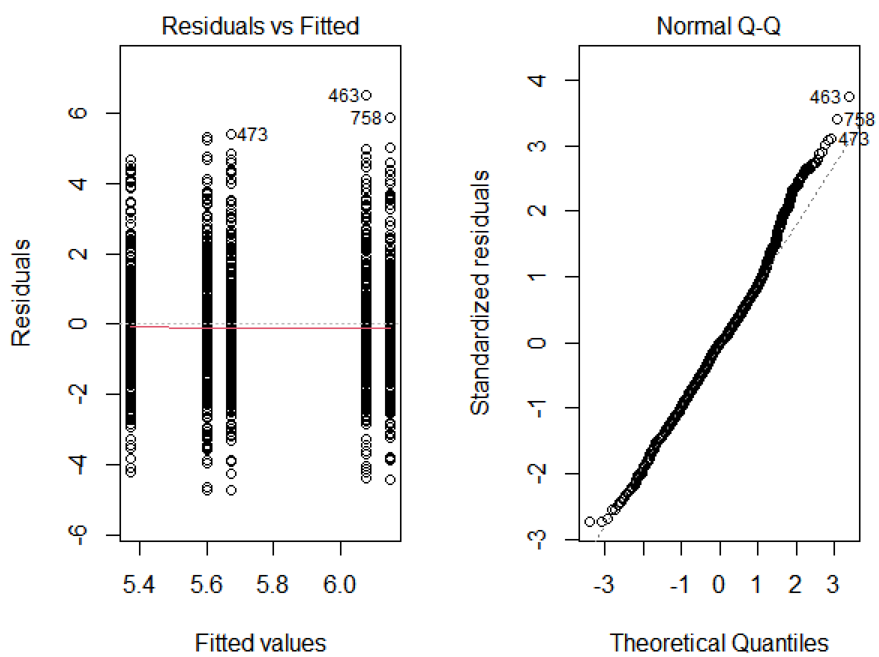
To lessen the right skewness of the data, we performed a square-root transformation on the response, Total Points. After performing a one-way ANOVA, we can see the role of the player has a significant effect on the total number of points a player receives at the $\alpha = 0.05$ level of significance.

We now want to determine *which* levels differ from each other in the Roles factor. Therefore, we will employ the Tukey's Honest Significant Differences (HSD) multiple comparison test to quantify the differences across levels to determine which levels in the Roles factor significantly differ from one another. The Tukey's HSD test will perform a pairwise comparison of all possible group combinations and test these pairs for significant differences in their means, all while adjusting the p-value to a higher threshold for significance to account for the fact that many statistical tests are being performed and the chance of a false positive increases with increasing number of tests.

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = sqrt(Total_Points) ~ Roles, data = player.games)

$Roles
                         diff         lwr       upr     p adj
Jungler-Support   0.22862552 -0.15697392 0.6142250 0.4851608
Top-Support       0.29775436 -0.08974262 0.6852513 0.2211190
Mid-Support       0.77584846  0.38737748 1.1643194 0.0000006
AD Carry-Support  0.70481352  0.31795641 1.0916706 0.0000072
Top-Jungler       0.06912884 -0.31515725 0.4534149 0.9881822
Mid-Jungler       0.54722294  0.16195474 0.9324911 0.0010349
AD Carry-Jungler  0.47618799  0.09254714 0.8598288 0.0064359
Mid-Top           0.47809410  0.09092674 0.8652615 0.0068370
AD Carry-Top      0.40705915  0.02151112 0.7926072 0.0325132
AD Carry-Mid     -0.07103495 -0.45756189 0.3154920 0.9871890
```

The results from the Tukey's HSD test shows there are six combinations of levels that have statistically significant differences at the $\alpha = 0.05$ level of significance: Mid & Support, AD Carry & Support, Mid & Jungler, AD Carry & Jungler, Mid & Top, and AD Carry & Top. Furthermore, the combination of Mid and Support resulted in the greatest difference, with a difference of 9.022.

We utilize diagnostic plots to determine whether the model meets the assumption of homoscedasticity.



The residual plot illustrates that the mean of the residuals is nearly horizontal and centered around zero, indicating that the model is free of large outliers that might induce bias. The normal Q-Q plot illustrates that the model's actual residuals are very similar to the theoretical residuals of a perfectly homoscedastic model. As a result of these diagnostic plots, the model fits the assumption of homoscedasticity.

3.2 Player Data: Factor Analysis on Kills, Deaths, Assists, and Creep Kills

For this question, we want to determine if the number of kills, deaths, assists, creep kills, and their interactions significantly influence the total number of points a player receives. Furthermore, we want to determine if there are significant differences in how the levels for each factor contributes to the total points a player receives. We chose to investigate these specific criteria since they are an accurate indicator of an individual's performance.

We initially consider a 4-factor multi-way layout model including all interaction terms:

$$\begin{aligned} y_{ijkl} =& \mu + \tau_i + \beta_j + \gamma_k + \delta_l + (\tau\beta)_{ij} + (\tau\gamma)_{ik} + (\tau\delta)_{il} + (\beta\gamma)_{jk} + (\beta\delta)_{jl} \\ &+ (\gamma\delta)_{kl} + (\tau\beta\gamma)_{ijk} + (\tau\beta\delta)_{ijl} + (\tau\gamma\delta)_{ikl} + (\beta\gamma\delta)_{jkl} + (\tau\beta\gamma\delta)_{ijkl} + \epsilon_{ijkl} \end{aligned}$$

where μ is the overall mean, τ_i is the kills effect, β_j is the deaths effect, γ_k is the assists effect, and δ_l is the creep kills effect.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
Kills	2	144.83	72.41	345.464	< 2e-16	***
Deaths	2	2.77	1.39	6.610	0.00139	**
Assists	2	140.43	70.22	334.988	< 2e-16	***
Creep_Kills	2	17.73	8.87	42.304	< 2e-16	***
Kills:Deaths	4	3.04	0.76	3.627	0.00601	**
Kills:Assists	4	30.53	7.63	36.418	< 2e-16	***
Deaths:Assists	4	2.00	0.50	2.381	0.04974	*
Kills:Creep_Kills	4	3.48	0.87	4.145	0.00242	**
Deaths:Creep_Kills	4	3.05	0.76	3.632	0.00595	**
Assists:Creep_Kills	4	10.92	2.73	13.024	2.02e-10	***
Kills:Deaths:Assists	8	3.02	0.38	1.802	0.07256	.
Kills:Deaths:Creep_Kills	7	0.97	0.14	0.664	0.70282	
Kills:Assists:Creep_Kills	6	1.52	0.25	1.208	0.29922	
Deaths:Assists:Creep_Kills	8	4.75	0.59	2.832	0.00404	**
Kills:Deaths:Assists:Creep_Kills	10	2.06	0.21	0.981	0.45810	
Residuals	1424	298.48	0.21			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

We performed a logarithm transformation on the response, Total Points, to stabilize the increasing variance. After performing a 4-factor multi-way ANOVA, we see kills, deaths, assists, and creep kills are all have a significant effect on the total number of points a player receives at the $\alpha = 0.05$ level of significance. Furthermore, there are several interaction terms that have a significant effect on the total number of points a player receives at the $\alpha = 0.05$ level of significance.

Therefore, we reduce the original model and consider the following model:

$$y_{ijkl} = \mu + \tau_i + \beta_j + \gamma_k + \delta_l + (\tau\beta)_{ij} + (\tau\gamma)_{il} + (\beta\gamma)_{jk} + (\tau\delta)_{il} + (\beta\delta)_{jl} + (\gamma\delta)_{kl} + (\beta\gamma\delta)_{jkl} + \epsilon_{ijkl}$$

```
                             Df Sum Sq Mean Sq F value   Pr(>F)    
Kills                         2 144.83   72.41 346.524  < 2e-16 ***
Deaths                        2   2.77    1.39   6.630  0.00136 ** 
Assists                       2 140.43   70.22 336.016  < 2e-16 ***
Creep_Kills                   2  17.73    8.87  42.434  < 2e-16 ***
Kills:Deaths                  4   3.04    0.76   3.638  0.00589 ** 
Kills:Assists                 4  30.53    7.63  36.529  < 2e-16 ***
Kills:Creep_Kills             4   3.50    0.87   4.183  0.00226 ** 
Deaths:Assists                4   1.98    0.49   2.363  0.05124 .  
Deaths:Creep_Kills            4   3.05    0.76   3.643  0.00583 ** 
Assists:Creep_Kills           4  10.92    2.73  13.064 1.86e-10 ***
Deaths:Assists:Creep_Kills    8   6.75    0.84   4.040 9.20e-05 ***
Residuals                  1455 304.05    0.21                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The interaction between deaths and assists are not significant at $\alpha = 0.05$. As a result, we can further simply the model to the following:

$$y_{ijkl} = \mu + \tau_i + \beta_j + \gamma_k + \delta_l + (\tau\beta)_{ij} + (\tau\gamma)_{il} + (\tau\delta)_{il} + (\beta\delta)_{jl} + (\gamma\delta)_{kl} + (\beta\gamma\delta)_{jkl} + \epsilon_{ijkl}$$

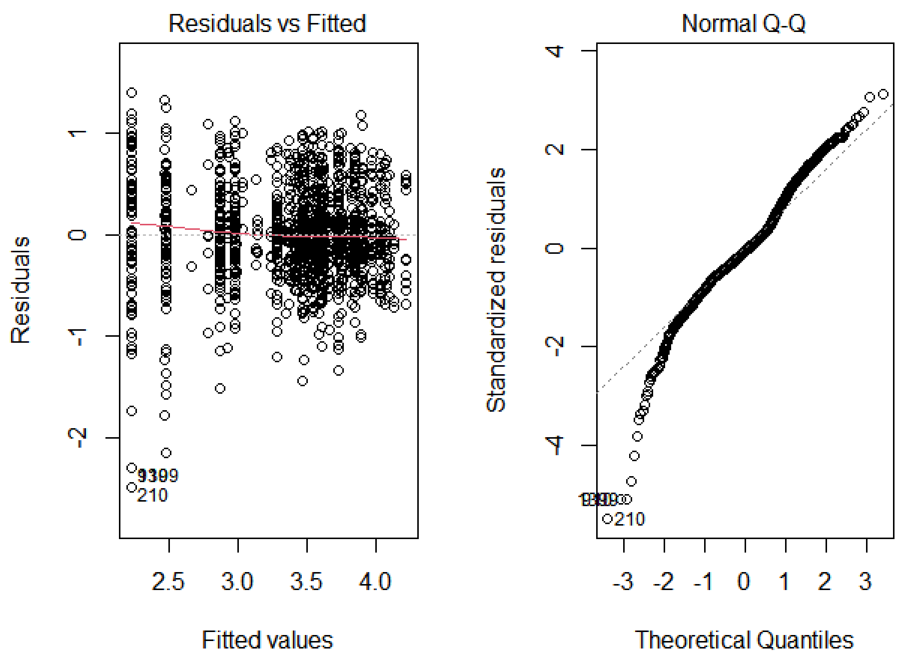
```
                             Df Sum Sq Mean Sq F value   Pr(>F)    
Kills                         2 144.83   72.41 346.524  < 2e-16 ***
Deaths                        2   2.77    1.39   6.630  0.00136 ** 
Assists                       2 140.43   70.22 336.016  < 2e-16 ***
Creep_Kills                   2  17.73    8.87  42.434  < 2e-16 ***
Kills:Deaths                  4   3.04    0.76   3.638  0.00589 ** 
Kills:Assists                 4  30.53    7.63  36.529  < 2e-16 ***
Kills:Creep_Kills             4   3.50    0.87   4.183  0.00226 ** 
Deaths:Creep_Kills            4   2.70    0.67   3.226  0.01200 *  
Assists:Creep_Kills           4  11.31    2.83  13.530 7.84e-11 ***
Deaths:Assists:Creep_Kills   12   8.69    0.72   3.465 4.65e-05 ***
Residuals                  1455 304.05    0.21                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

We now want to determine *which* levels differ from each other in their respective factor by using Tukey's HSD test.

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = log(Total_Points) ~ Kills + Deaths + Assists + Creep_Kills + Kills:Deaths + Kills:Assists + Kills:Creep_Kills + Deaths:Creep_Kills + Assists:Creep_Kills + 
Deaths:Assists:Creep_Kills, data = player.games)

$Kills
                 diff       lwr       upr p adj
Medium-Low  0.5092994 0.4451876 0.5734113     0
High-Low    0.7631302 0.6855616 0.8406988     0
High-Medium 0.2538308 0.1682033 0.3394582     0

$Deaths
                    diff         lwr         upr     p adj
Medium-Low  -0.087136440 -0.14546567 -0.02880721 0.0013669
High-Low    -0.079962854 -0.18038675  0.02046104 0.1483817
High-Medium  0.007173586 -0.09459794  0.10894511 0.9850367

$Assists
                 diff       lwr       upr p adj
Medium-Low  0.4990188 0.4363187 0.5617190     0
High-Low    0.7813408 0.7039074 0.8587743     0
High-Medium 0.2823220 0.2083105 0.3563335     0

$Creep_Kills
                   diff         lwr         upr     p adj
Medium-Low   0.22451438  0.16116334  0.28786541 0.0000000
High-Low     0.06981067 -0.00509374  0.14471507 0.0738064
High-Medium -0.15470371 -0.22687463 -0.08253279 0.0000017
```

The results from the Tukey's HSD tests shows all combinations of levels for the kills and assists factors have statistically significant differences at $\alpha = 0.05$ level of significance. For the deaths factor, only medium & low deaths have a statistically significant difference. Finally, for the creep kills factor, the combination of medium & low and high & medium have statistically significant differences.

We utilize diagnostic plots to determine whether the model meets the assumption of homoscedasticity.



The residual plot is satisfactory. The left end of the Q-Q plot is potentially problematic, but overall, the actual residuals are close to the theoretical residuals. For that reason, we find that the model meets the assumption of homoscedasticity.

3.3 Per Team Role Analysis

For this question, we want to determine if there are significant differences in how each role contributes to the total points for each team. Also, we want to determine if these differences are consistent across each team.

We consider a 7-factor multi-way layout model, without interaction terms for simplicity:

$$y_{ijklmnpq} = \mu + \tau_i + \beta_j + \gamma_k + \delta_l + \zeta_m + \eta_n + \theta_p + \epsilon_q$$

where μ is the overall mean, τ_i is the role effect, β_j is the kills effect, γ_k is the deaths effect, δ_l is the assists effect, ζ_m is the creep kills effect, η_n is the opponent effect, and θ_p is the player effect. The square-root of the response variable was used in order to stabilize the variance of the residuals.

Running this model for each team and checking the ANOVA results indicated that Role is a significant feature for most teams, but not all of them. Role contrasts were performed for each role pair and each team when applicable, the results are summarized in the table below.

Contrast	Significant Count	Sig Mean Difference
Jungle - Support	1	0.9724
Top - Support	2	0.7710
Mid - Support	12	0.9408
AD Carry - Support	13	0.9469
Top - Jungler	1	0.7075
Mid - Jungler	7	0.8816
AD Carry - Jungler	5	0.8519
Mid - Top	5	0.9707
AD Carry - Top	4	0.7400
AD Carry - Mid	4	-0.07557

The diagnostics plots for these comparisons are all sufficient and are shown in the **Supplementary Section**.

From the table it is clear that AD Carry and Mid are most significantly different from Support, indicating that these two roles have a greater contribution to the Total Points for the team than Support. Other roles were significantly different for a minority of teams. The fact that Role is not a significant feature for some teams is an indication that those teams' Roles all contributed equally to the Total Points the team received, and no one player stood out more than others.

3.4 30-Minute Win Analysis

For this question we want to determine which features are most important in achieving a 30-minute win.

We consider a 4-factor multi-way layout model with interaction terms:

$$y_{ijklm} = \mu + \tau_i + \beta_j + \gamma_k + \delta_l + (\tau\beta)_{ij} + (\tau\gamma)_{ik} + (\tau\delta)_{il} + (\beta\gamma)_{jk} + (\beta\delta)_{jl} + (\gamma\delta)_{kl} + \epsilon_m$$

where μ is the overall mean, τ_i is the First Blood effect, β_j is the Towers Destroyed effect, γ_k is the Dragons Killed effect, and δ_l is the Barons Killed effect.

In this model, our response variable is the binary response variable 30-min win. Below shows the ANOVA results for the complete model:

```
Response: thirty_min_win
                                            Df Sum Sq Mean Sq F value    Pr(>F)    
First_Bloods                                 3  0.593 0.19780  0.7155 0.5435910    
Dragon_Kills                                 2  4.213 2.10662  7.6202 0.0006198 ***
Baron_Kills                                  2  3.946 1.97294  7.1367 0.0009771 ***
Towers_Destroyed                             2  4.688 2.34421  8.4797 0.0002771 ***
First_Bloods:Dragon_Kills                    6  1.165 0.19424  0.7026 0.6477550    
First_Bloods:Baron_Kills                     6  2.189 0.36483  1.3197 0.2489649    
Dragon_Kills:Baron_Kills                     4  0.098 0.02459  0.0890 0.9858417    
First_Bloods:Towers_Destroyed                5  1.243 0.24870  0.8996 0.4820254    
Dragon_Kills:Towers_Destroyed                3  0.242 0.08078  0.2922 0.8310106    
Baron_Kills:Towers_Destroyed                 3  0.080 0.02678  0.0969 0.9616946    
First_Bloods:Dragon_Kills:Baron_Kills        8  5.246 0.65581  2.3722 0.0178570 *  
First_Bloods:Dragon_Kills:Towers_Destroyed   3  1.200 0.40009  1.4473 0.2297184    
First_Bloods:Baron_Kills:Towers_Destroyed    5  1.665 0.33310  1.2049 0.3075016    
Dragon_Kills:Baron_Kills:Towers_Destroyed    3  0.286 0.09524  0.3445 0.7931594    
Residuals                                  238 65.795 0.27645                      
```

Each of the individual factors excluding First Bloods is significant, and the only significant interaction term is the interaction between the three significant features. When the model was built again with only the significant factors and the significant interaction term, the interaction term became insignificant. Therefore we used the reduced model and use TukeyHSD at $\alpha = 0.05$ to perform hypothesis testing between the different factor levels in each feature:

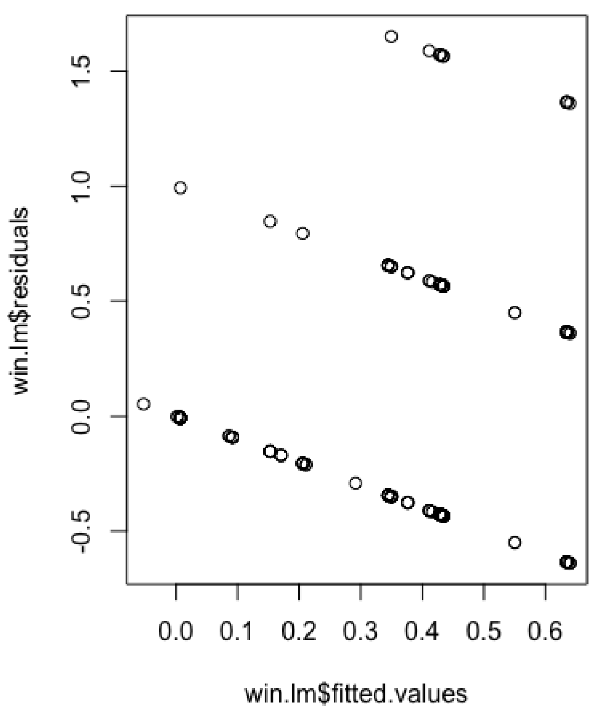
$$y_{ijkl} = \mu + \beta_i + \gamma_j + \delta_k + \epsilon_l$$

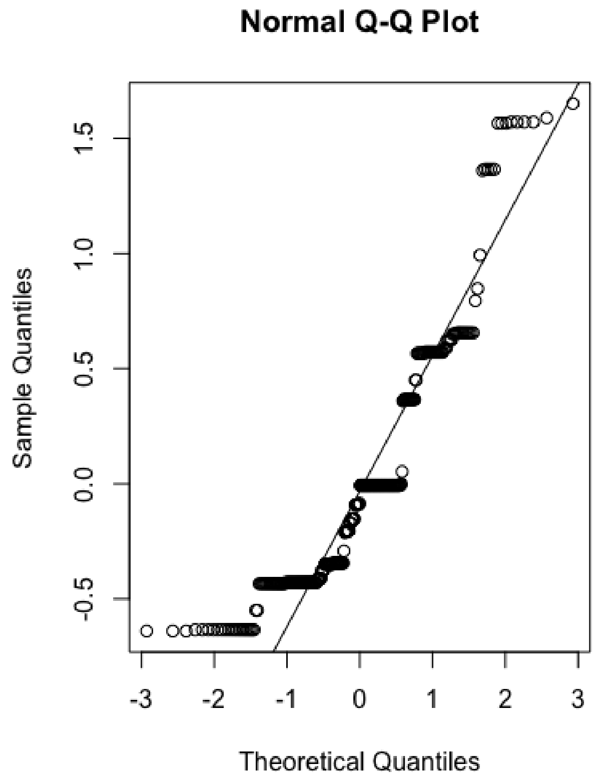
```
Fit: aov(formula = thirty_min_win ~ Dragon_Kills + Baron_Kills + Towers_Destroyed, data = team.games)

$Dragon_Kills
                   diff         lwr        upr     p adj
Medium-Low   0.24826389  0.09753567 0.39899211 0.0003796
High-Low     0.02414773 -0.26222104 0.31051650 0.9784794
High-Medium -0.22411616 -0.50814197 0.05990965 0.1526301

$Baron_Kills
                   diff         lwr       upr     p adj
Medium-Low   0.22390863  0.07055952 0.3772577 0.0019269
High-Low     0.02952914 -0.23581514 0.2948734 0.9628209
High-Medium -0.19437949 -0.45351038 0.0647514 0.1825206

$Towers_Destroyed
                 diff         lwr       upr     p adj
Medium-Low  0.1259687 -0.05276960 0.3047071 0.2223443
High-Low    0.2365824  0.02976501 0.4433997 0.0203176
High-Medium 0.1106136 -0.06645502 0.2876823 0.3060581
```

The hypothesis testing results indicate one significant factor level difference for each feature:

- Dragon Kills: There is a significantly different effect between getting a Medium number of Dragon Kills and a Low number
- Baron Kills: There is a significantly different effect between getting a Medium number of Baron kills and a Low number
- Towers Destroyed: There is a significantly different effect by destroying a High number of towers opposed to a Low number

The diagnostics plot for this model are shown in the plots below:





It is apparent these diagnostics plots do not pass our assumptions of constant variance and normal residuals. From the appearance of the fitted values vs residuals, there is a missing factor or interaction influencing the data. We were not able to find another significant feature that, when added to the model, achieved appropriate diagnostics. The conclusions of these hypothesis tests are therefore questionable.

4 Conclusions

Per Player Role Analysis: We conclude that a player's role has a significant impact on the total number of points the player receives. Furthermore, we found there are significant differences between several combinations of roles, with the combination of Mid and Support having the greatest difference.

Factor Analysis on Kills, Deaths, Assists, and Creep Kills for Player Data: We discovered that a player's total amount of points is heavily influenced by the number of kills, deaths, assists, and creep kills. Some interaction terms were found to be significant as well. We were also able to determine that there are significant differences in how the levels of their respective factors contribute to a player's total points. The initial 4-factor multi-way ANOVA model had to be modified twice to contain only significant terms.

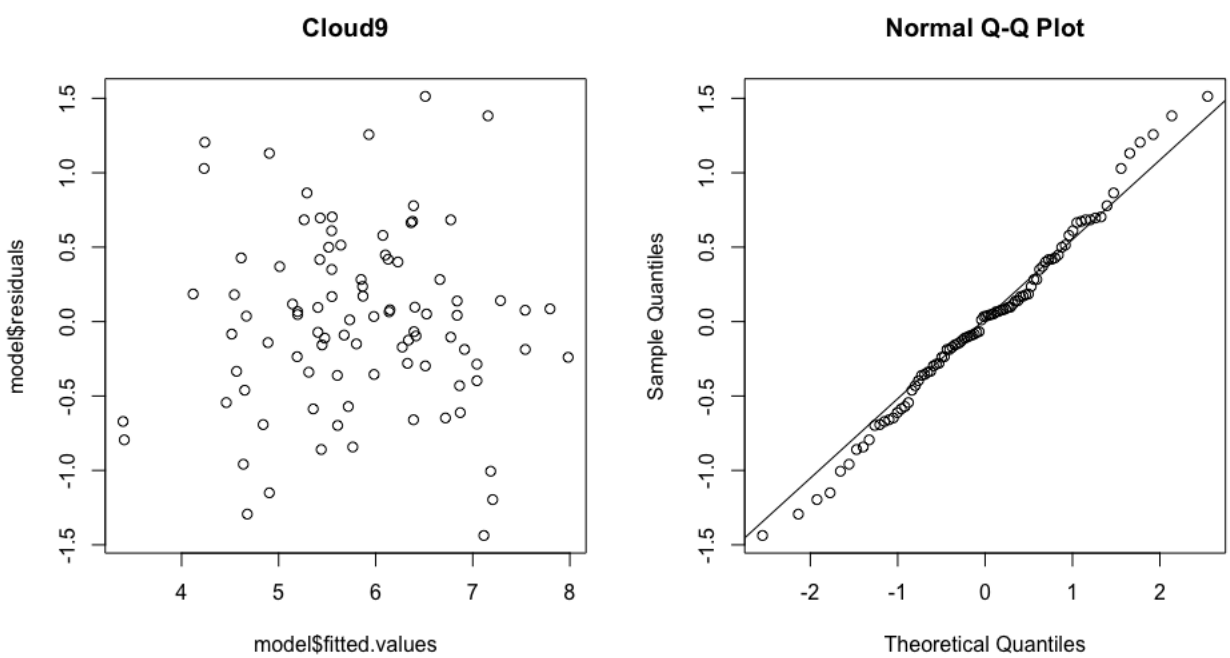
Per Team Role Analysis: We conclude that a player's role was important for the majority of teams, but not all of them. Furthermore, it became evident that ADC and Mid differ the most from Support, implying that these roles contribute more to a team's total points than Support.

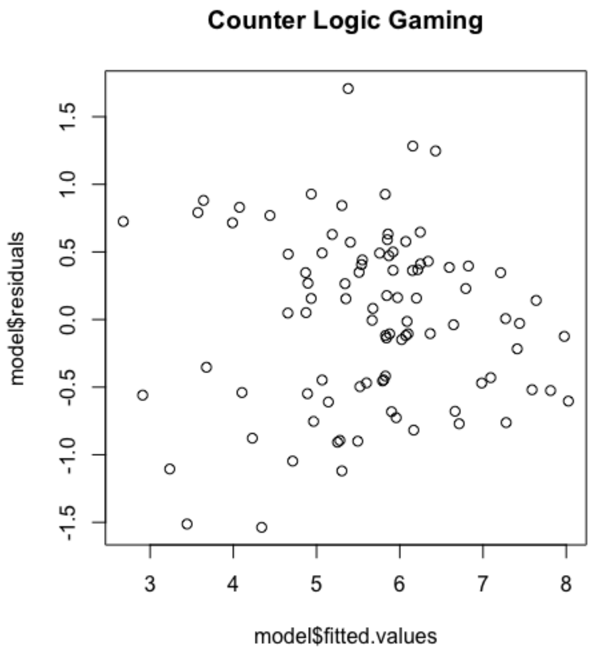
30-Minute Win Analysis: We conclude that the amount of dragon kills, Baron kills, and towers destroyed have a significant impact on the likelihood of a 30-minute victory. All interaction terms were found to be insignificant after modifying the original model twice to only include significant factors. There was only one combination of levels that exhibited a significant difference for each factor. However, because the diagnostic plots for the model failed to pass the homoscedasticity assumptions, our conclusions in this section are questionable.

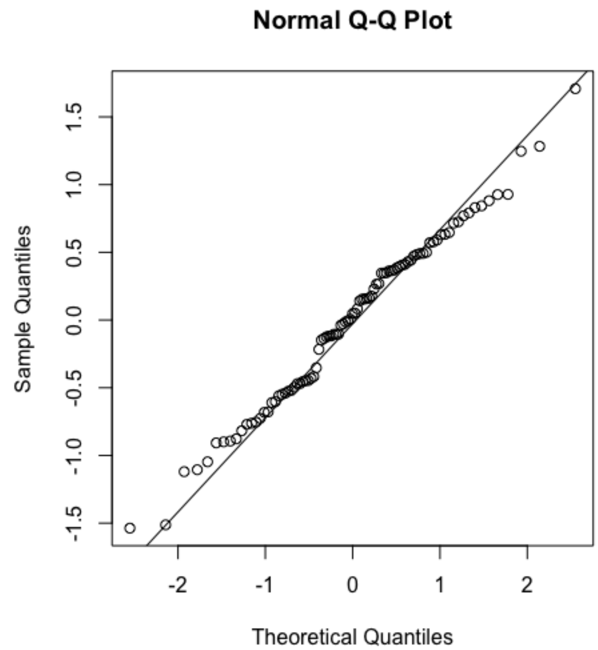
5 Supplementary

5.1 Per-Team Role Analysis

Diagnostic Plots for Per Team Role Analysis




Counter Logic Gaming
model$residuals
model$fitted.values
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5
3
4
5
6
7
8


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5
-2
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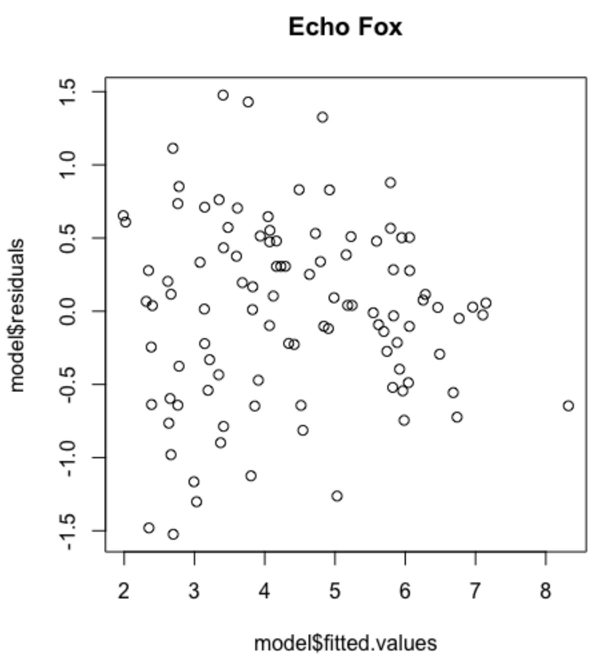
2


Echo Fox
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model$fitted.values
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2
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5
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7
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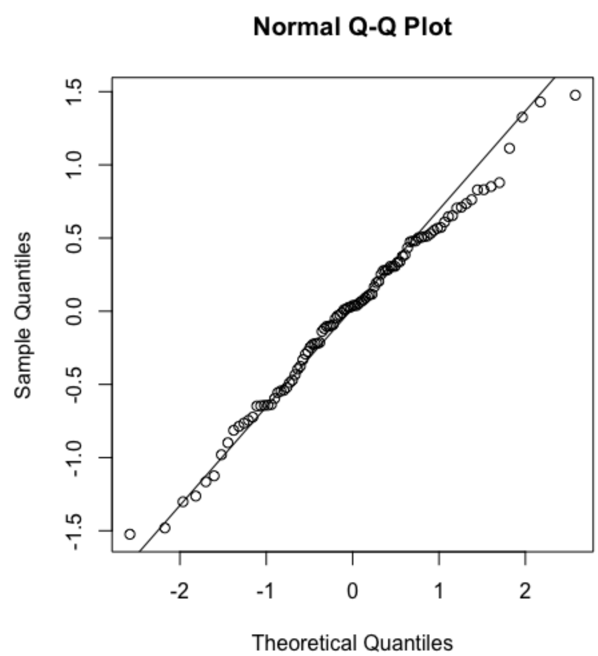
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
-1.5
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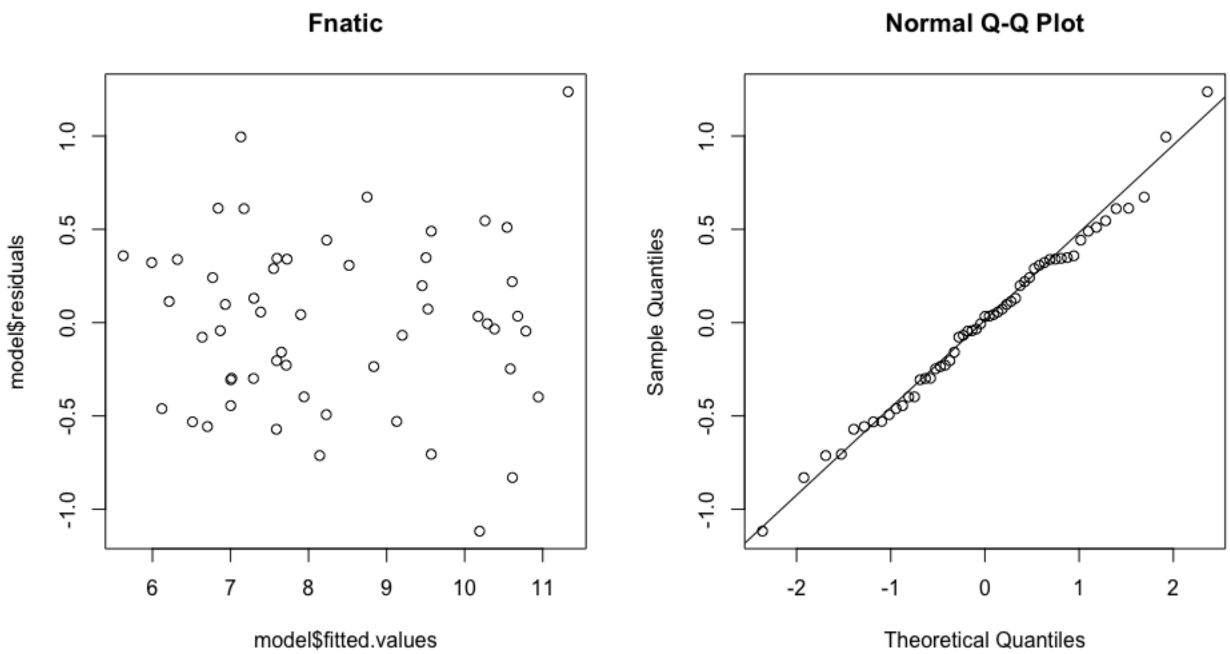
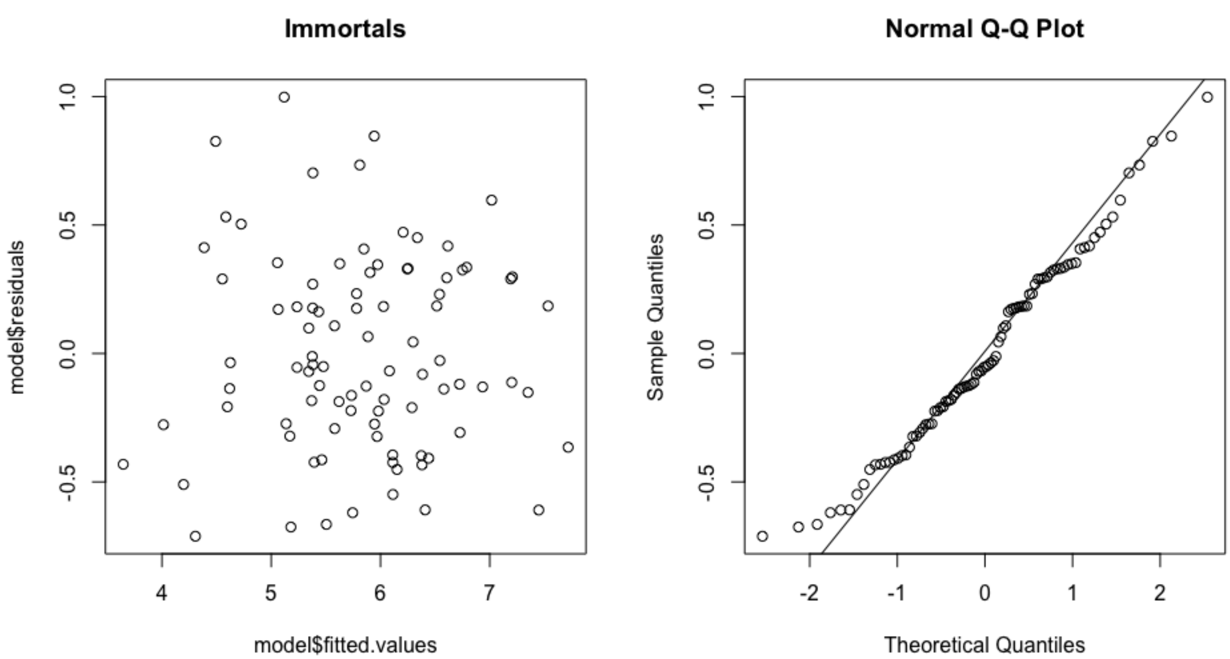
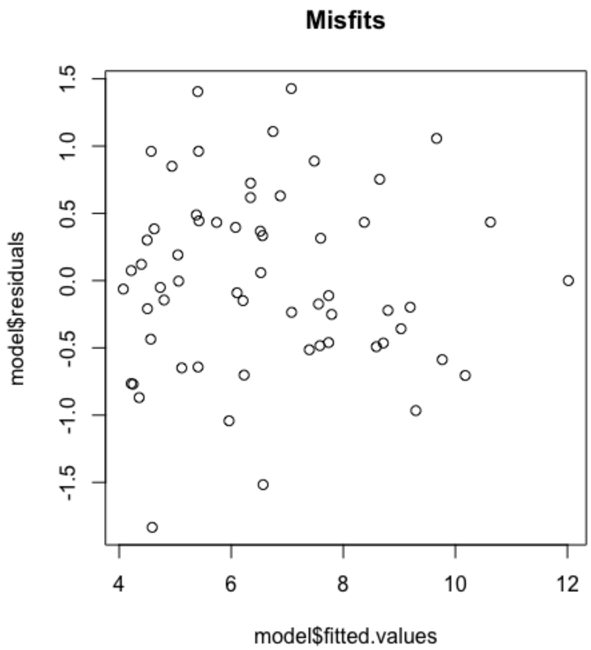
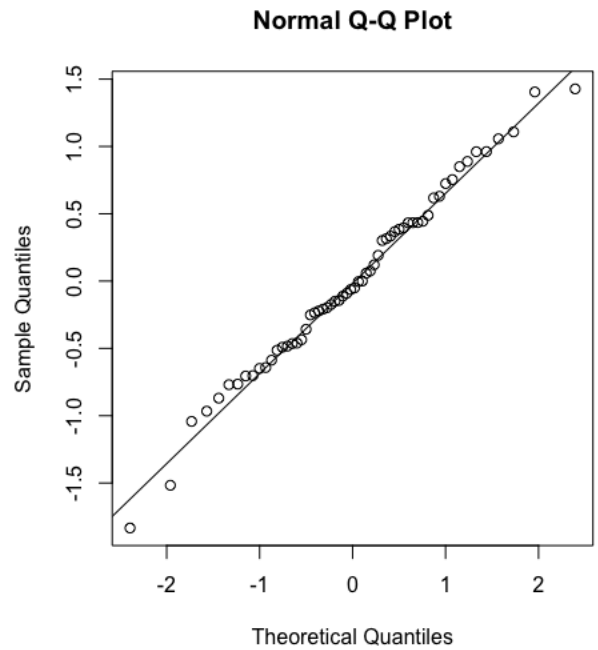
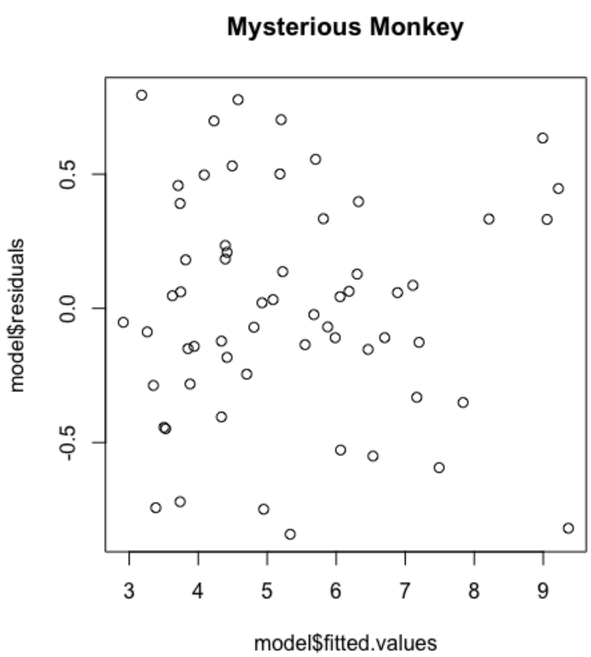
-0.5
0.0
0.5
1.0
1.5
-2
-1
0
1
2

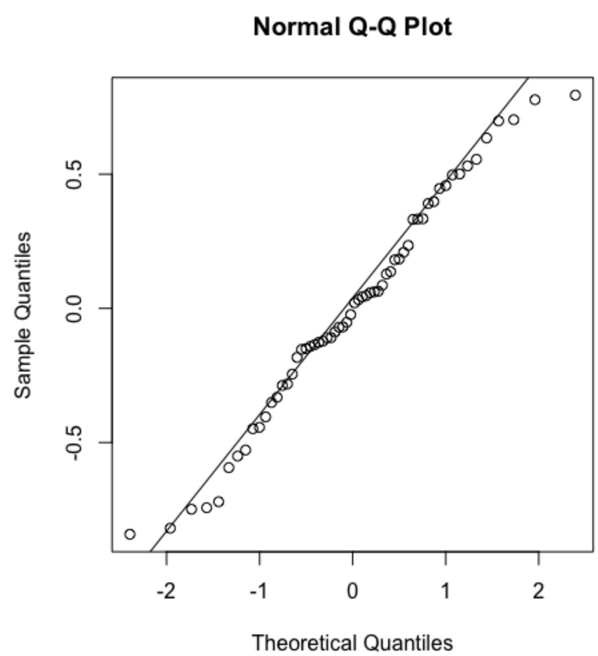

Fnatic
model$residuals
model$fitted.values
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles

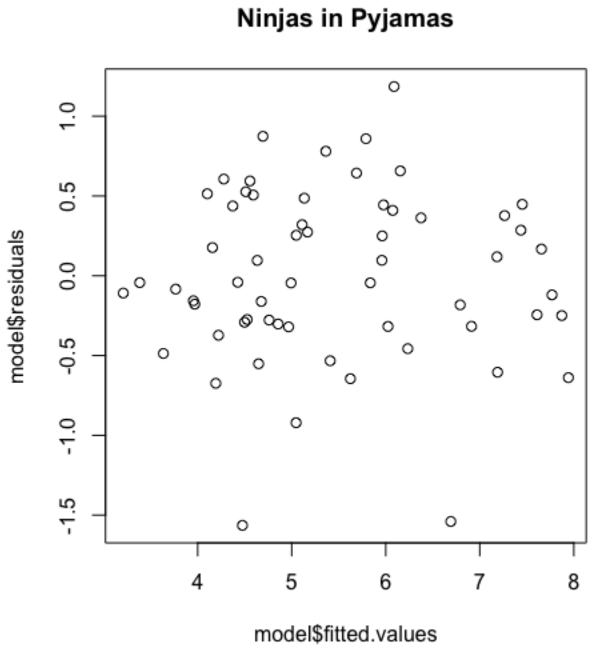

Immortals
model$residuals
model$fitted.values
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles

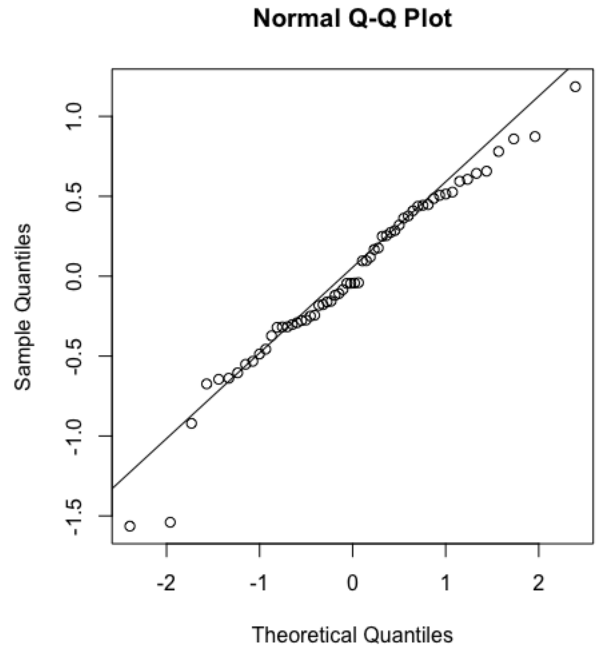

Misfits
model$residuals
model$fitted.values


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles


Mysterious Monkey
model$residuals
model$fitted.values


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles


Ninjas in Pyjamas
model$residuals
model$fitted.values
-1.5
-1.0
-0.5
0.0
0.5
1.0
4
5
6
7
8


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
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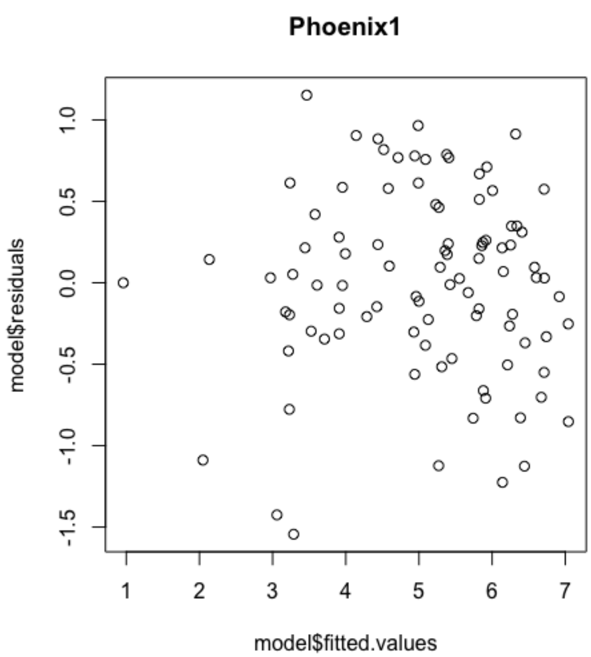
0
1
2


Phoenix1
model$residuals
model$fitted.values
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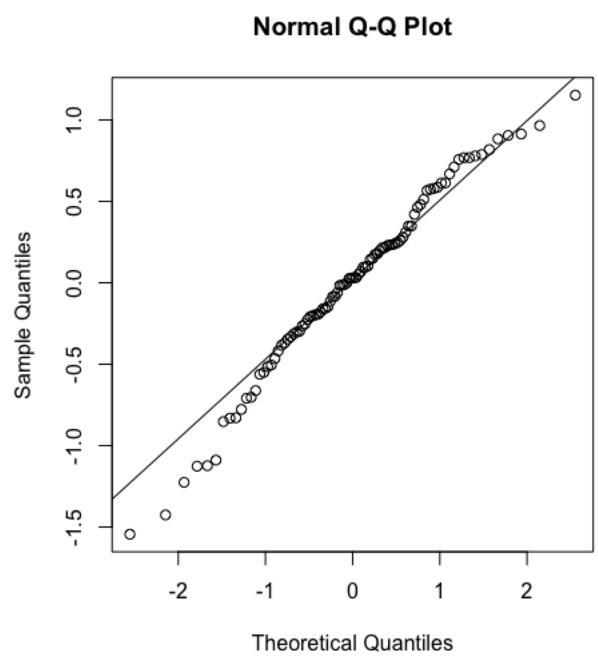
4
5
6
7


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
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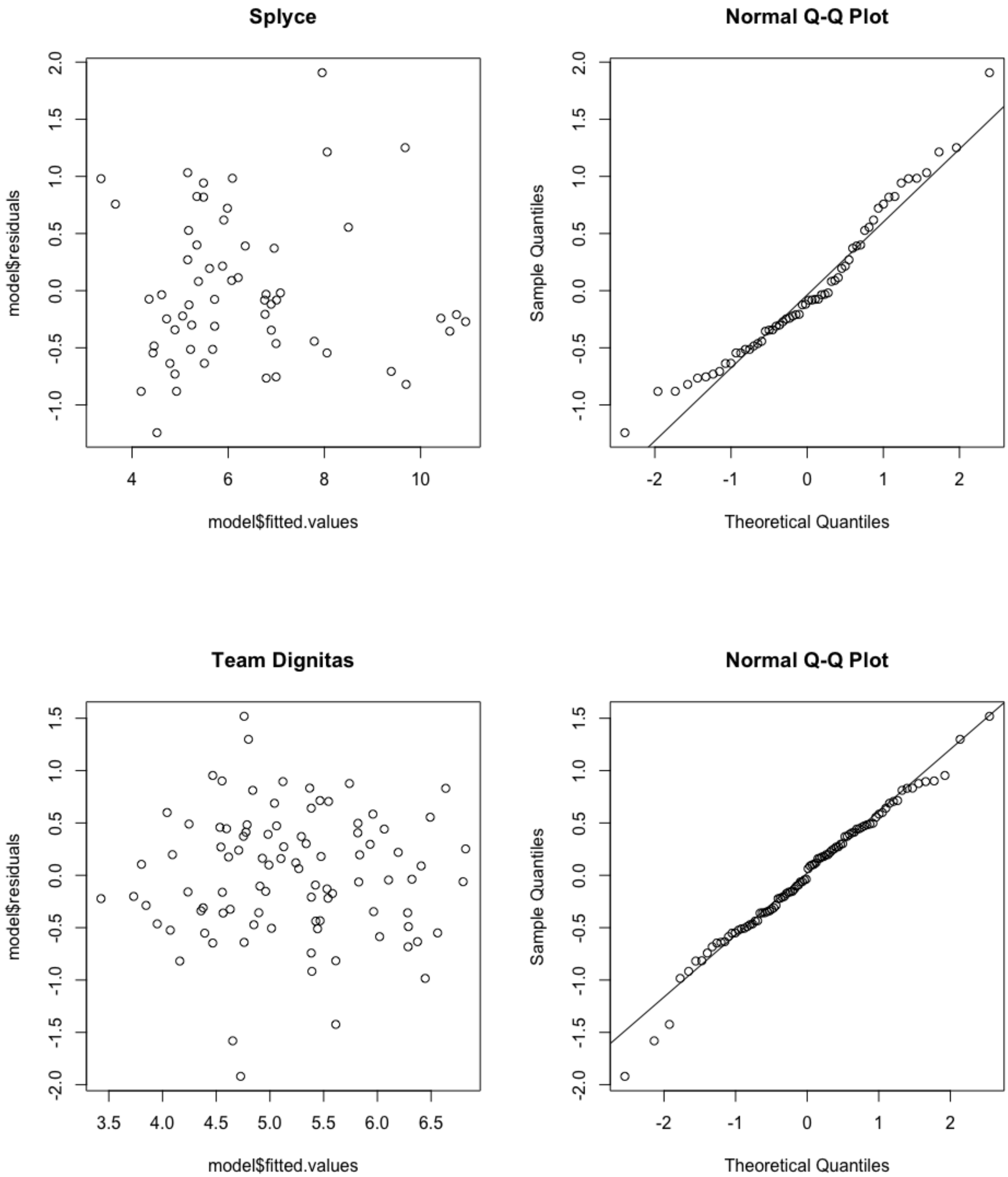
-1
0
1
2


Splyce
model$residuals
model$fitted.values
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1.0
0.5
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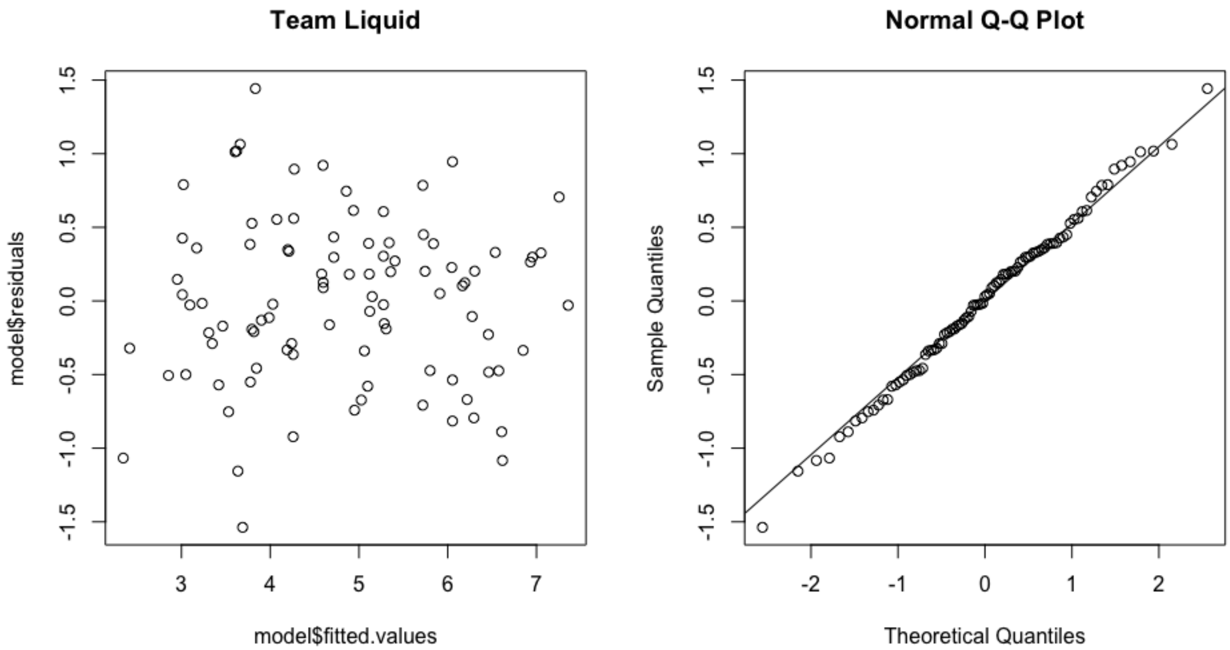
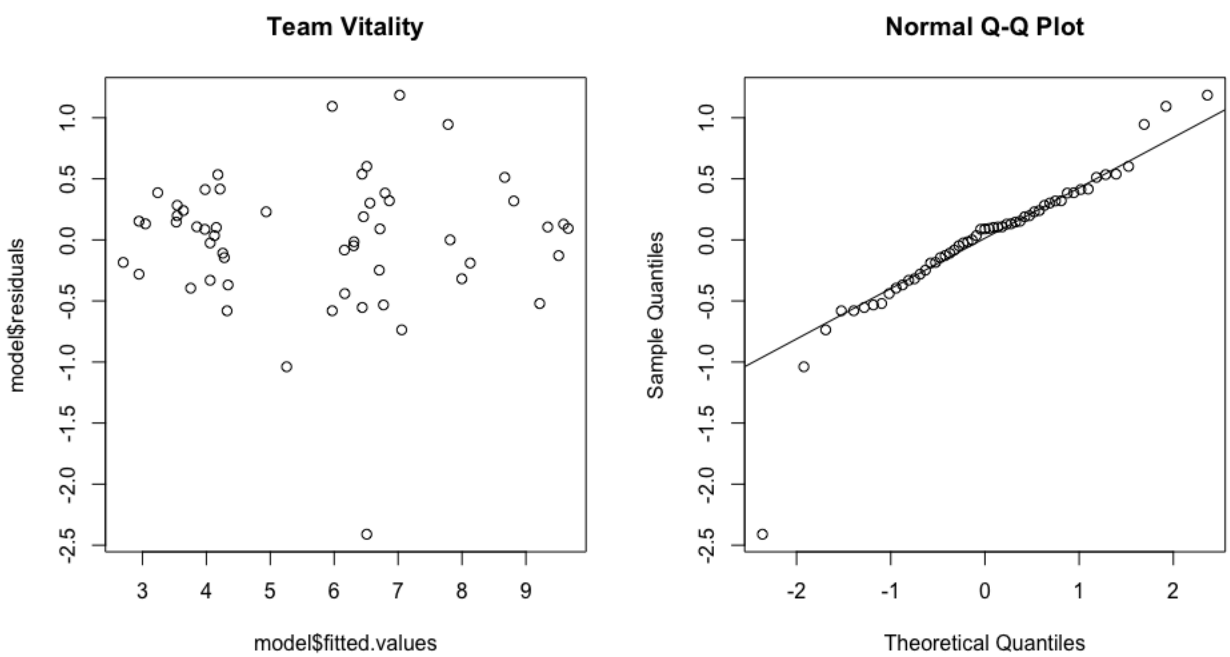
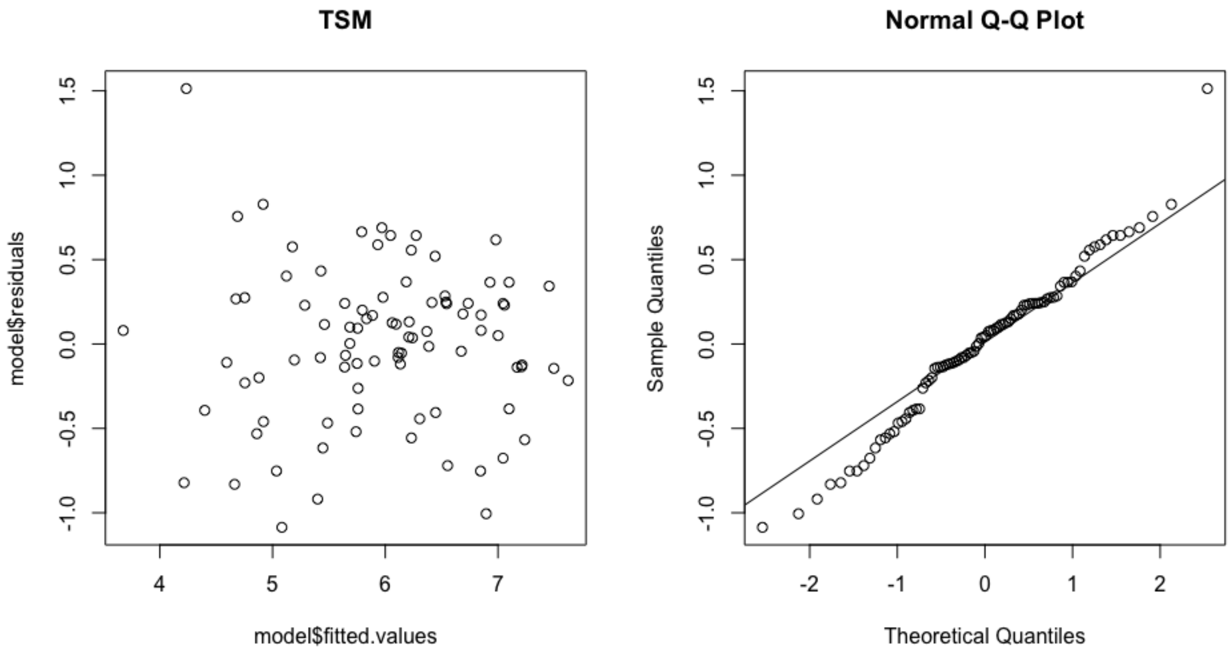
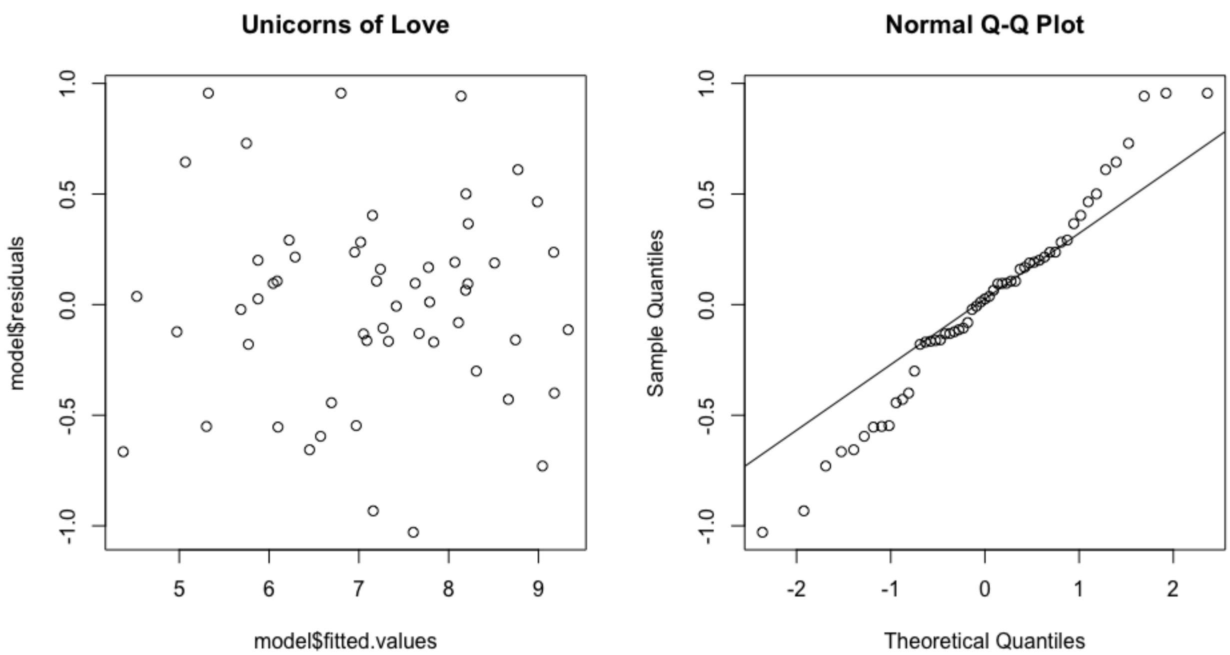
-0.5
-1.0
4
6
8
10
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
-2
-1
0
1
2
Team Dignitas
model$residuals
model$fitted.values
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
3.5
4.0
4.5
5.0
5.5
6.0
6.5
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles


Team Liquid
model$residuals
model$fitted.values
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles


Team Vitality
model$residuals
model$fitted.values
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles





ANOVA Results per Team

```
[1] "Cloud9"
Analysis of Variance Table
```

```
Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4 21.416  5.3539 11.6004 2.784e-07 ***
Kills        2 19.292  9.6459 20.8998 7.639e-08 ***
Deaths       2  2.819  1.4093  3.0535   0.05353 .
Assists      2 18.091  9.0455 19.5989 1.742e-07 ***
Creep_Kills  2  0.724  0.3620  0.7844   0.46038
opponent     8 17.997  2.2497  4.8744 8.363e-05 ***
Name         1  2.140  2.1403  4.6374   0.03473 *
Residuals   70 32.307  0.4615
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Counter Logic Gaming"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4 19.193  4.7983  9.1483 5.102e-06 ***
Kills        2 26.764 13.3821 25.5140 4.470e-09 ***
Deaths       2  2.621  1.3106  2.4987   0.08940 .
Assists      2 40.354 20.1772 38.4695 4.805e-12 ***
Creep_Kills  2 14.251  7.1256 13.5856 1.010e-05 ***
opponent     8 10.822  1.3527  2.5791   0.01566 *
Name         1  0.328  0.3284  0.6261   0.43142
Residuals   71 37.239  0.5245
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Echo Fox"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4 21.291   5.323 10.6107 6.957e-07 ***
Kills        2 83.187  41.593 82.9140 < 2.2e-16 ***
Deaths       2  5.049   2.524  5.0323  0.008863 **
Assists      2 72.372  36.186 72.1350 < 2.2e-16 ***
Creep_Kills  2 13.864   6.932 13.8187 7.608e-06 ***
opponent     8  9.204   1.150  2.2934  0.029436 *
Name         4  1.775   0.444  0.8847  0.477263
Residuals   76 38.125   0.502
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "FlyQuest"
Analysis of Variance Table
```

```
Response: sqrt(Total_Points)
           Df Sum Sq Mean Sq F value    Pr(>F)
Roles       4  6.570  1.6426  6.8120  0.000111 ***
Kills       2 35.139 17.5696 72.8614 < 2.2e-16 ***
Deaths      2  8.051  4.0255 16.6938 1.221e-06 ***
Assists     2 35.492 17.7460 73.5928 < 2.2e-16 ***
Creep_Kills  2  2.758  1.3789  5.7183  0.005037 **
opponent    8 13.881  1.7351  7.1955 6.873e-07 ***
Residuals  69 16.638  0.2411
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Fnatic"
Analysis of Variance Table

Response: sqrt(Total_Points)
           Df Sum Sq Mean Sq F value    Pr(>F)
Roles       4  9.502  2.3756  7.2747 0.0002254 ***
Kills       2 22.191 11.0955 33.9777 6.307e-09 ***
Deaths      1  9.694  9.6940 29.6861 4.121e-06 ***
Assists     2 16.185  8.0926 24.7821 1.974e-07 ***
Creep_Kills  2  4.031  2.0156  6.1723 0.0050579 **
opponent    8 72.429  9.0536 27.7250 5.812e-13 ***
Residuals  35 11.429  0.3266
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "G2 Esports"
Analysis of Variance Table

Response: sqrt(Total_Points)
           Df Sum Sq Mean Sq F value    Pr(>F)
Roles       4  5.936   1.484  2.2199   0.08974 .
Kills       2 26.000  13.000 19.4449 3.370e-06 ***
Deaths      2 46.831  23.416 35.0242 1.111e-08 ***
Assists     2 18.923   9.461 14.1521 4.298e-05 ***
Creep_Kills  2 66.183  33.091 49.4967 2.240e-10 ***
opponent    8 45.301   5.663  8.4699 4.959e-06 ***
Name        2  0.171   0.085  0.1278   0.88049
Residuals  31 20.725   0.669
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "H2K"
Analysis of Variance Table

Response: sqrt(Total_Points)
           Df Sum Sq Mean Sq F value    Pr(>F)
```

```
Roles        4  1.996   0.499  0.5559  0.696119
Kills        2 65.585  32.793 36.5242 3.406e-09 ***
Deaths       2 13.728   6.864  7.6450  0.001812 **
Assists      2 61.156  30.578 34.0572 7.597e-09 ***
Creep_Kills  2  7.041   3.520  3.9210  0.029358 *
opponent     8 54.300   6.787  7.5598 9.362e-06 ***
Residuals   34 30.526   0.898
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Immortals"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df  Sum Sq Mean Sq F value    Pr(>F)
Roles        4  8.9216  2.2304  11.961 1.938e-07 ***
Kills        2 20.5372 10.2686  55.070 5.071e-15 ***
Deaths       2  8.0849  4.0425  21.680 4.946e-08 ***
Assists      2 15.0170  7.5085  40.268 2.580e-12 ***
Creep_Kills  2  3.7939  1.8970  10.173 0.0001343 ***
opponent     8  5.6193  0.7024   3.767 0.0010311 **
Residuals   69 12.8660  0.1865
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Misfits"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4 16.063   4.016  5.7974 0.0009244 ***
Kills        2 66.998  33.499 48.3610 2.748e-11 ***
Deaths       2 24.994  12.497 18.0412 2.836e-06 ***
Assists      2 48.675  24.337 35.1349 1.884e-09 ***
Creep_Kills  2  0.338   0.169  0.2442 0.7845314
opponent     8 53.932   6.741  9.7323 2.677e-07 ***
Residuals   39 27.015   0.693
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Mysterious Monkeys"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4 10.040  2.5099  9.1583 3.017e-05 ***
Kills        2 53.369 26.6847 97.3699 1.816e-15 ***
Deaths       2  8.507  4.2535 15.5207 1.275e-05 ***
```

```
Assists      2 33.055 16.5276 60.3077 2.271e-12 ***
Creep_Kills  2  2.066  1.0331  3.7698   0.03235 *
opponent     8 52.059  6.5074 23.7449 2.312e-12 ***
Name         2  2.107  1.0534  3.8437   0.03043 *
Residuals   37 10.140  0.2741
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Ninjas in Pyjamas"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  9.772  2.4431  5.7432 0.0009484 ***
Kills        2 13.814  6.9069 16.2366 6.881e-06 ***
Deaths       1  1.326  1.3255  3.1160 0.0851628 .
Assists      2 21.188 10.5941 24.9043 9.437e-08 ***
Creep_Kills  2  6.767  3.3834  7.9536 0.0012355 **
opponent     8 40.631  5.0789 11.9393 1.660e-08 ***
Residuals   40 17.016  0.4254
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Phoenix1"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  8.452   2.113  4.8083 0.0017839 **
Kills        2 63.260  31.630 71.9743 < 2.2e-16 ***
Deaths       2  1.163   0.581  1.3230 0.2730951
Assists      2 50.695  25.347 57.6780 2.256e-15 ***
Creep_Kills  2  7.293   3.646  8.2973 0.0005966 ***
opponent     8 15.745   1.968  4.4783 0.0002123 ***
Name         5  5.135   1.027  2.3368 0.0510846 .
Residuals   68 29.884   0.439
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Team Envy"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  4.399  1.0998  2.3388  0.063864 .
Kills        2 36.782 18.3912 39.1099 4.956e-12 ***
Deaths       2  6.648  3.3242  7.0691  0.001625 **
Assists      2 39.106 19.5532 41.5811 1.600e-12 ***
```

```
Creep_Kills  2  0.293  0.1467  0.3120  0.733042
opponent     8 19.518  2.4397  5.1883 4.497e-05 ***
Name         1  0.599  0.5995  1.2748  0.262836
Residuals   68 31.977  0.4702
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "ROCCAT"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  6.638  1.6595  2.3308   0.07571 .
Kills        2 45.430 22.7151 31.9044 1.580e-08 ***
Deaths       2  2.300  1.1502  1.6155   0.21367
Assists      2 47.082 23.5409 33.0643 1.061e-08 ***
Creep_Kills  2  1.321  0.6604  0.9275   0.40531
opponent     8 63.114  7.8893 11.0808 1.548e-07 ***
Residuals   34 24.207  0.7120
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Splyce"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  9.173  2.2934  3.8105   0.01023 *
Kills        2 51.274 25.6372 42.5970 1.229e-10 ***
Deaths       1  0.206  0.2063  0.3428   0.56152
Assists      2 60.893 30.4467 50.5881 1.112e-11 ***
Creep_Kills  2  5.950  2.9752  4.9434   0.01206 *
opponent     8 64.979  8.1223 13.4955 3.154e-09 ***
Residuals   40 24.074  0.6019
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Team Dignitas"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  7.031  1.7577  3.6309 0.0096775 **
Kills        2  9.347  4.6734  9.6536 0.0002040 ***
Deaths       2  3.666  1.8332  3.7867 0.0275901 *
Assists      2 13.123  6.5617 13.5541 1.111e-05 ***
Creep_Kills  2  1.301  0.6505  1.3437 0.2677189
opponent     8 18.603  2.3254  4.8034 0.0001037 ***
```

```
Name         3  1.318  0.4393  0.9075 0.4421146
Residuals   68 32.920  0.4841
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Team Liquid"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4 13.670   3.417  7.9992 2.335e-05 ***
Kills        2 70.211  35.105 82.1725 < 2.2e-16 ***
Deaths       2  3.575   1.787  4.1836  0.019280 *
Assists      2 29.000  14.500 33.9411 5.449e-11 ***
Creep_Kills  2  3.802   1.901  4.4498  0.015217 *
opponent     8 18.311   2.289  5.3578 3.016e-05 ***
Name         5  7.176   1.435  3.3593  0.008963 **
Residuals   69 29.478   0.427
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Team Vitality"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  9.898  2.4745  5.2704  0.002058 **
Kills        2 52.765 26.3825 56.1908 1.667e-11 ***
Deaths       2 28.541 14.2705 30.3941 2.694e-08 ***
Assists      2 44.550 22.2752 47.4429 1.451e-10 ***
Creep_Kills  2  1.742  0.8710  1.8552  0.171913
opponent     8 78.161  9.7702 20.8090 5.368e-11 ***
Residuals   34 15.964  0.4695
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "TSM"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df  Sum Sq Mean Sq F value    Pr(>F)
Roles        4 10.1594  2.5398  9.4647 3.695e-06 ***
Kills        2 12.7797  6.3899 23.8117 1.368e-08 ***
Deaths       2  7.7807  3.8903 14.4972 5.544e-06 ***
Assists      2 16.6904  8.3452 31.0982 2.355e-10 ***
Creep_Kills  2  5.6665  2.8332 10.5580 9.992e-05 ***
opponent     8 12.0441  1.5055  5.6103 1.759e-05 ***
Residuals   69 18.5161  0.2683
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[1] "Unicorns of Love"
Analysis of Variance Table

Response: sqrt(Total_Points)
            Df Sum Sq Mean Sq F value    Pr(>F)
Roles        4  6.626  1.6566  5.2186  0.002183 **
Kills        2  0.187  0.0934  0.2942  0.746992
Deaths       2 14.771  7.3853 23.2657 4.303e-07 ***
Assists      2  7.890  3.9452 12.4284 8.884e-05 ***
Creep_Kills  2  3.307  1.6536  5.2093  0.010630 *
opponent     8 53.019  6.6273 20.8780 5.131e-11 ***
Residuals   34 10.793  0.3174
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```