Identifying Symbiotic Relationships between Champions in League of Legends

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Abstract
League of Legends (LoL) is a multiplayer online battle arena game where teams of five players compete against each other. Over the years, players have formed a metagaming strategy, consisting of five distinct roles, which has been widely adopted. This study uses logistic regression models to identify symbiotic relationships (such as Mutualism, Commensalism, and Parasitic) between two of the roles: Attack Damage Carries (ADC) and Supports. We use an adaptation of the traditional regression adjusted plus minus model commonly used in other sports for this study. Results from the 2015 LoL North American Ranked season indicate only 5% of observed champion pairs are beneficial to both the ADC and Support and these pairs made up over 10% of matches played. Further, about 28% of pairs had at least one of the ADC of Support be negatively impacted and they made up over 40% of observed matches. Win rates for Mutualism and Commensalism pairs were substantially higher than the other categories.

Key Words: sports; esports; video games; amateur

1. Introduction

Esports games have become more popular over the past decade both professionally and casually, with revenue expected to exceed one billion USD in 2019[1]. One of the most successful esports games is a Multiplayer Online Battle Arena (MOBA) game called *League of Legends* (LoL) by Riot Games. League of Legends was released in late 2009, and in 2017 (the most recent year of data) over 100 million players played it on a monthly basis[2].

Typical game play in the flagship mode called "Summoner's Rift" consists of participants picking in-game characters (called champions[3] in LoL) and form two teams of five to compete on a map consisting of three lanes (and the surrounding area called the jungle). Over the years, players have formulated a strategy, commonly referred to as metagaming (Carter, Gibbs, and Harrop 2012). In LoL, metagaming strategy (also known as meta) is a product of the wisdom of the crowd, and it has stabilized to a team of five unique roles: (Solo) Top, Jungle, (Solo) Mid, Attack damage carry (aka "ADC"), and Support. Figure 1

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[1] https://newzoo.com/insights/articles/newzoo-global-esports-economy-will-top-1-billion-for-the-first-time-in-2019
[2] https://rankedkings.com/blog/how-many-people-play-league-of-legends
[3] As of May 2019 there were 144 champions. See https://na.leagueoflegends.com/en/game-info/champions/ for the complete list.

shows how the typical meta roles distribute themselves amongst the three lanes (and jungle) on the LoL map.

Figure 1: Map of Summoner's Rift game mode with meta role designations.

The bottom lane in Summoner's Rift is the only region in which two players on the same team regularly share the same space. As a result, champions played in the two meta roles, Attack Damage Carry (ADC) and Support, should pick two champions that complement each other. In particular, Table 1 breakdowns some of the complementary design aspects of these characters.

Table 1: Examples of complementary design aspects between ADCs and Support champions

ADC	Support
• Heavily dependent on optimizing lane resources (such as minion kills) to increase their power	• Is not as dependent on items to increase fighting potential
• Weak in early game, can "carry team" if powered up properly	• Initial goal is to assist their more vulnerable teammate (i.e., the ADC) through the earliest stages of the game
• Cannot easily create kill opportunities	• Creates kill opportunities for the ADC

One interesting gameplay aspect of LoL is learning which champions work well with one another when on the same team and which do not. Historically, players have in-game experience or from fan sites that make suggestions[4]. Several data-driven studies about team compositions exist and they tend to focus on the interaction of champions and/or use machine-learning algorithms to identify viable team compositions. See Chen et al. (2018), da Costa Oliveira et al. (2017), Lee and Ramler (2017), and Lee and Ramler, (2019) as recent examples. However, many of these studied use methods that limit the understanding of each individual's contribution and do not attempt to dig deeper into the composition of the interaction.

[4] See https://www.reddit.com/r/leagueoflegends/comments/43xm9h/useful_lol_websites_and_resources_2016_edition/ for a list of example fan sites

In this paper, we define models that separately measures the impact on game performance metrics when using “champion A” given that it is paired with “champion B” (and vice versa). This conditional modeling approach treats the two involved champions as separate entities allowing for relationships to be more broadly classified than just whether or not the pair is synergistic[5]. More specifically, we apply this idea to modeling win rates between Attack Damage Carries (ADC) champions and Support champions using *League of Legends* data made available by Lee and Ramler (2017).

The rest of this paper is as follows: Section 2 defines the methodology used in classifying champion pairs, Section 3 highlights some of the main results of the applying the methodology to the *League of Legends* data, and Section 4 summarizes our findings and outlines considerations for future work.

2. Methodology

The basic goal of the approach is to build a series of conditional models to better understand the nature of the interaction between ADC champions and Support champions. In essence, each ADC will have their own model with predictors for each Support and vice versa.

More formally, for each match involving the $ith\ ADC$, let

$$S_{j|i} = \begin{cases} 1 & ADC_i \text{ and } Support_j \text{ are on the team together} \\ 0 & \text{otherwise} \end{cases}.$$

Then, we formulate a GLM:

$$\omega_i = \beta_{0|i} + \beta_{1|i}S_{1|i} + \cdots + \beta_{j|i}S_{j|i} + \beta_{J|i}S_{J|i},$$

where the family and link are appropriate for the chosen response.
(For example, $\omega_i = \ln\left(\frac{p_i}{1-p_i}\right)$ is the logit link for win rates (p_i) of ADC_i.)

We then construct a similar set of models using Support as the condition and ADCs as the predictors.

i.e., for each match involving the jth Support, let

$$A_{i|j} = \begin{cases} 1 & ADC_i \text{ and } Support_j \text{ are on the team together} \\ 0 & \text{otherwise} \end{cases},$$

and the GLM be represented by

$$\nu_j = \eta_{0|j} + \eta_{1|j}A_{1|j} + \cdots + \eta_{i|j}A_{i|j} + \eta_{I|j}A_{I|j}.$$

The regression coefficients ($\beta_{j|i}$) measure the impact on win rates of the i^{th} ADC being paired with Support *j*. Positive regression coefficients indicate that the ADC benefits from a particular Support while negative values indicate that the ADC does not benefit. The regression coefficients defined for the Support models ($\eta_{i|j}$) can be interpreted in a similar way.

[5] In a classic interaction model, being synergistic would imply a positive slope coefficient on the interaction term between two champions.

One advantage of separate models for ADC and Supports is that this allows us to estimate one-way relationships between champions. Thus, the relationship between ADC by Support pairs can be viewed in a similar fashion to symbiosis in biological organisms (Morin, 2011). Figure 2 displays the symbiosis terminology and Table 2 shows its connection to the ADC-Support models.

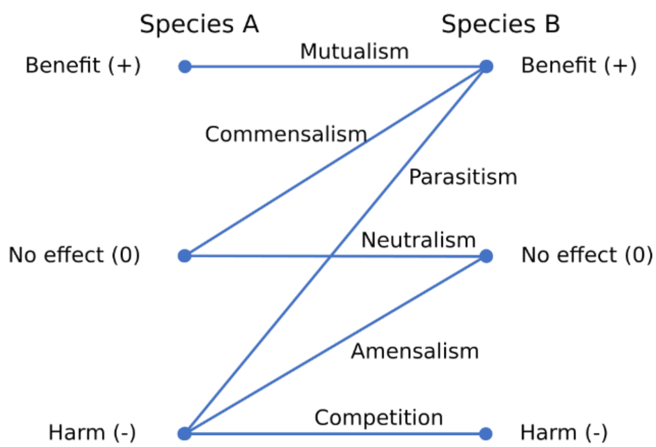

Figure 2: Chart of symbiotic relationship terms between two organisms[6].

Table 2: Connection between symbiotic relationship and ADC by Support pairs

Relationship	Connection to models
Mutualism	Both $\beta_{j\|i}$ and $\eta_{i\|j}$ are greater than zero
Commensalism	One slope coefficient is positive, the other is zero
Neutralism/Regular	Both $\beta_{j\|i}$ and $\eta_{i\|j}$ are equal to zero
Amensalism	One slope coefficient is negative, the other is zero
Parasitic	One slope coefficient is positive, the other is negative
Competitive	Both $\beta_{j\|i}$ and $\eta_{i\|j}$ are less than zero

3. Results

Using the above methodology, we constructed models based on the 2015 Ranked Solo and Ranked Team data collected by Lee and Ramler (2017). It consisted of 19 Supports and 17 ADCs (all that were in the game at the time) and all 323 ADC by Support pairs were observed. Sample sizes used in the models ranged from roughly 13,000 for the least popular champions to 700,000 for the most popular. We classified the ADC by Support relationships into one of the six categories based on whether or not a Bonferroni adjusted p-value associated with the regression coefficient ($\beta_{j|i}$ or $\eta_{i|j}$) is less than 0.05. The models were then used to make predictions across the four tiers of competition (called "queues") in LoL: Ranked Team, Ranked Solo, Normal Draft, and Normal Blind.

[6] By Ian Alexander - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=71067142

The fifth column in figure 3 shows that the majority of ADC by Support pairs were classified as having a “regular relationship” (white). Only about 5% of pairs (17 of 323) were beneficial to both the ADC and Support (Mutualism, dark green) while another 14% were beneficial to one without negatively impacting the other (Commensalism, light green). About 28% were in either a Parasitic, Amensalism, or Competitive relationship. Further, as seen in the first four columns the percent of matches with each type of pair was relatively consistent across queues. In them, about 25 – 30% of matches are beneficial (green) while over 40 – 45% of matches contain harmful relationships (purple).

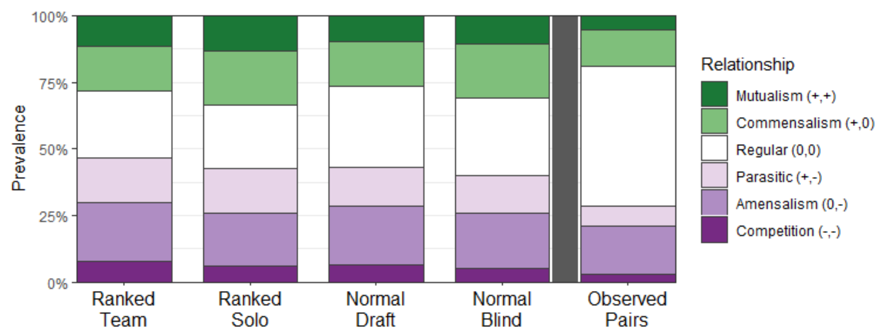

Figure 3: Prevalence of each ADC by Support relationship category. The first four columns represent the percent of observed matches in each category across the competition tiers. The last column is the percent of the 323 pairs in each category.

Figure 4 displays the win rates across the relationship categories for each queue type. Not surprisingly, those with benefial pairing had higher rates (about 53% for mutualism) while this decreased to around 45 - 47% for competition. The variability in win rates across the relationships was slightly less for the most competitive queue, Ranked Team.

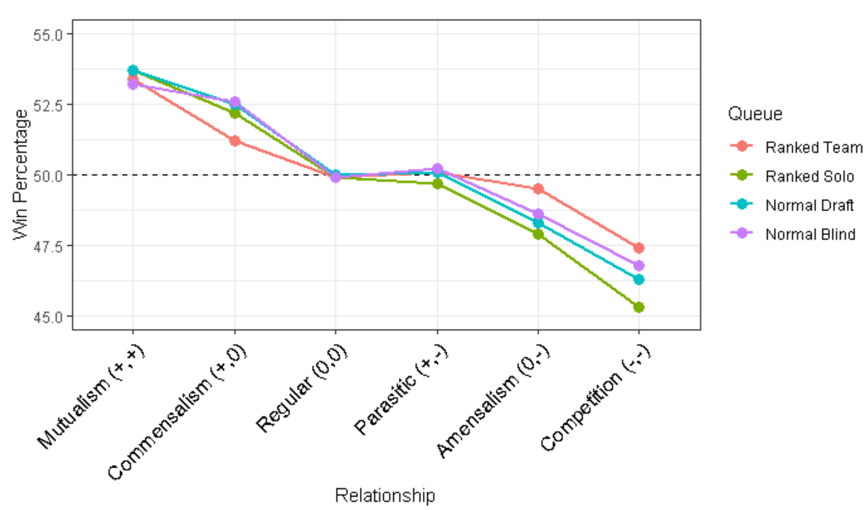

Figure 4: Win percentage for each category across the different queues.

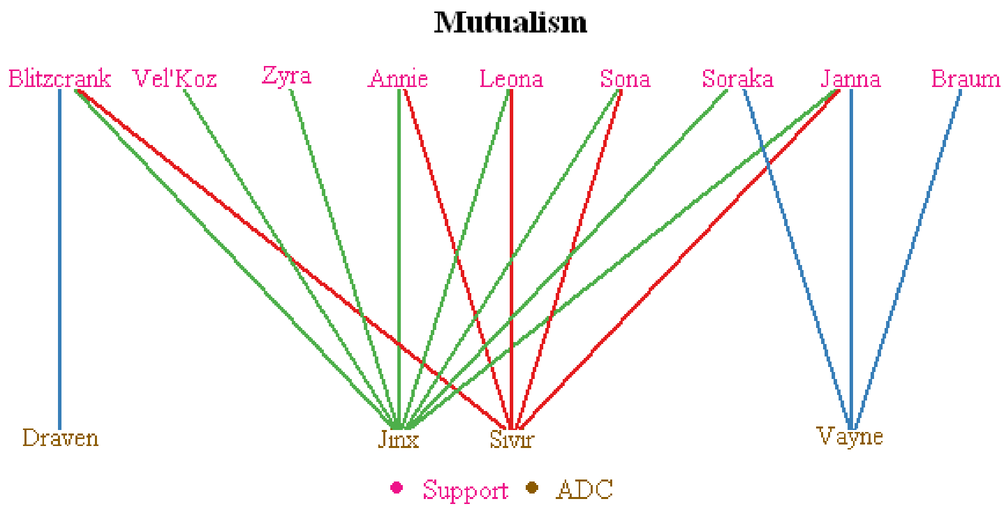

Figure 5: Bipartite graph representing the Mutualism relationship pairs.

Figure 5 displays the 17 Mutualism pairs as spread across nine Supports and four ADCs. As seen in the figure, three ADCs (Jinx, Sivir, and Vayne) dominate the graph, with each having multiple Supports that they interact well with. A general tendency here seems that the many of the Support champions have abilities in which they slow, immobilize, or otherwise hinder an opposing champion. For example, Annie has an ability that will incapacitate opposing targets. ADCs like Jinx and Sivir each have abilities that can capitalize of the reduced movement of their enemy. (e.g., Sivir has a "boomerang" ability that can heavily damage a target twice if they remain in its path.)

Figures 6 – 9 in the Appendix show the equivalent relationship pairs for the Commensalism (Figure 6), Parasitic (Figure 7), Amensalism (Figure 8), and Competition (Figure 9) categories.

4. Discussion

The approach described here provides a way to show the potentially one-sided nature of relationships between ADCs and Supports in LoL. The general trends in the results indicated that while only a few pairs benefit greatly from each other, they are popular in play. Interestingly, the reverse is also true. Compared to the proportion of negative relationships out of the 323 observed pairs, the Competitive, Parasitic, and Amensalism pairs appear in over 40% of matches. This leads to a series of other interesting research questions for future work. In particular, with recent changes to what type of data is available, information about both the "selections and bans[7]" from a match can be obtained. This might give insight on the champion selection process of players and see if they are knowingly forgoing synergistic pairings. Another interesting question would be whether popular fan sites offer suggestions that are reflected in the data. For example, are they suggesting the pairs identified in the Mutual category (Figure 5) but missing out on those in the Commensalism (Figure 6)? Do they focus on counter picks[8] which can be thought of as a defensive move instead of attempting to pair their ADC and Support

[7] https://leagueoflegends.fandom.com/wiki/Draft_Pick

[8] http://forums.na.leagueoflegends.com/board/showthread.php?t=849597

together? These, and numerous others, are all questions that can be investigated to better understand champion selection in LoL.

The model described in Section 2 can be extended to investigate game statistics other than win rates. This may also have practical use for players as it can help them understand how pairs of champions interact. For example, win rates may measure *if* they interact, but do not answer *how* they interact. Additionally, the interaction partition models introduced in this paper could have applications in other esports as well as in other sports. Other potentially useful game statistics could be gold earned, minion kills, and structures destroyed. While not all of these metrics are available in the data used in this study, new data could be collected to investigate these. Finally, the method is easy to apply to new seasons of LoL and can be extended to other positions, other player rankings, and other games with similar character interactions such as *Overwatch*, *Defense of the Ancients 2*, and *Clash Royale*.

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A. Appendix

This appendix contains the bipartite graph representations for the, Commensalism, Parasitic, Amensalism, and Competition relationship pairings.

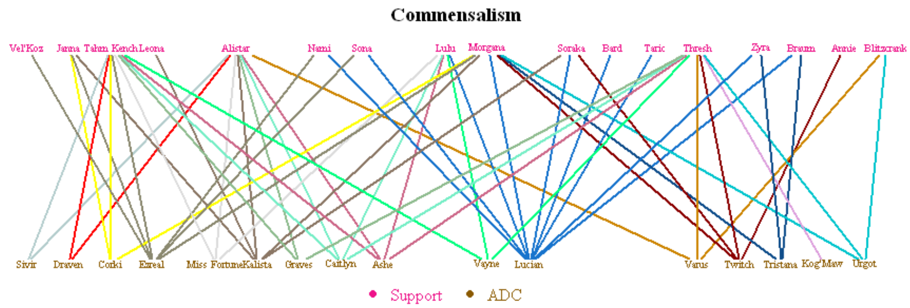

Figure 6: Bipartite graph representing the Commensalism relationship pairs.

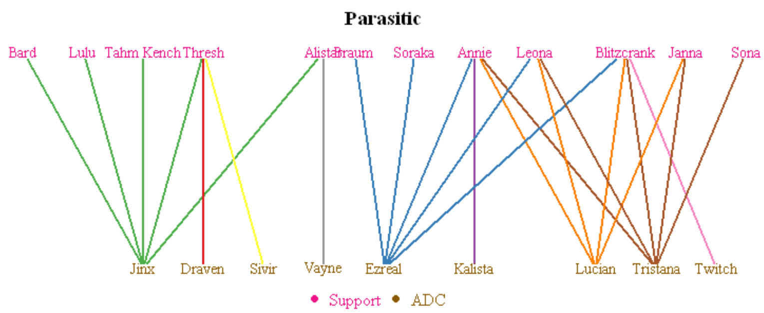

Figure 7: Bipartite graph representing the Parasitic relationship pairs.

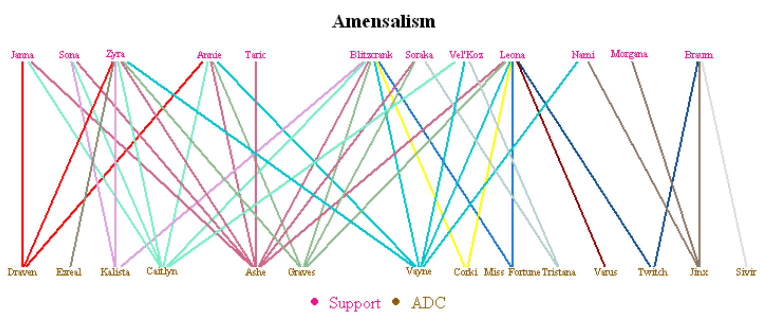

Figure 8: Bipartite graph representing the Amensalism relationship pairs.

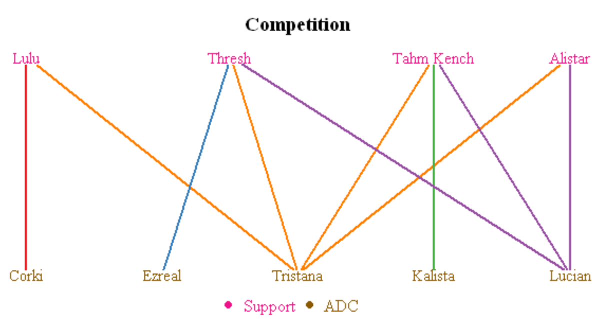

Figure 9: Bipartite graph representing the Competition relationship pairs.