Possible Open-Ended Strategy Selection in League of Legends

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Abstract

League of Legends is a popular online video game where players battle against one another to climb in skill rank. Since a single player will encounter only five of approximately a million opponents in any single match, a player must use good strategies to win matches. Players interact to form a directed network of strategies, which is functionally analogous to a social aggression hierarchy with strategies as nodes instead of individuals. The interactions between the players and game developers results in seemingly open-ended evolution of strategies over time, since the game developers change the game rules over time. To help identify if the strategies are open-ended to the extent that biological evolution is open-ended, the mechanisms of data generation are modeled as a system comprised of interacting subsystems. To better understand how strategies become popular via player-to-player interactions (under unchanging game rules), this project focuses on the relationship between the overall strategy network N and an individual players observation of the network n. While the structure of N is solely determined by player-to-player interactions, the behavior of individual players is influenced by their knowledge of N via n. This feedback loop contributes to the emergence of successful strategies, which evolve in a possibly open-ended manner within the entire game system as a whole. It is found that players with accurate representations of N are likely to experience less variability in their match outcomes, while players who have a less accurate representation have a large variety of match outcomes. Since players perpetuate successful strategies, this variability may contribute to the emergence of widespread usage (or lack thereof) of a particular strategy. Some correlation was found between the amount of variation a player has in selecting strategies and n.

Introduction

Arguably one of the most challenging scientific endeavors at the forefront of 21st century is the quest to understand how living systems differentiate themselves from non-living systems, namely how they are able to evolve and solve problems open-endedly. We currently have few insights into how living systems might *quantifiably* differ from their non-living counterparts, as in a mathematical foundation to explain away our observations of evolution, emergence, innovation, and organization. Development of a theory of living systems, if at all possible, demands mathematical understanding of how data is generated, collected, and changes over time like current, well-established scientific disciplines.

According to many philosophers who agree with Alfred N. Whitehead, the fault of these disciplines is the omission of crucial observations in order to satisfy a rigid mathematical approach. Current models that describe the precession of physical entities thorough space-time are not sufficient to understand the phenomenon that are more common to experiencing everyday life as humans(Whitehead, 1927, 1928, 1934), such as selecting our favorite t-shirt to wear for the day. Some of these phenomena (feelings, thoughts, the popularity of political candidates) are considered emergent behavior, which are what most agent-based modeling techniques aim to reproduce. Systems that undergo open-ended evolution have the additional requirement that they generate and utilize innovation, which is difficult to define. In most human-centric systems, emergence, open-ended evolution, and innovation are core mechanisms that have yet to be understood but drive the behavior of the system on several levels.

On the other hand, technology in today's (respectively more) globalized society is providing us with an overabundance of data. Because of this, we have seen recent work on understanding large-scale biological processes shift focus towards innovative, technological, and social systems. The evolution of patents(Chalmers et al., 2010; Buchanan et al., 2011) and online social systems(DeDeo, 2011; Oka and Ikegami, 2013; Oka et al., 2015) are just a few examples.

League of Legends as an Open-Ended System

League of Legends is a popular online video game where players battle against one another in teams to climb in skill rank. A player must be both cooperative with their own team, and aggressive against all players on the other team. In each match, players are randomly placed into two teams of five such that ten players of approximate skill level participate in a single match.

Since a single player will encounter five of approxi-

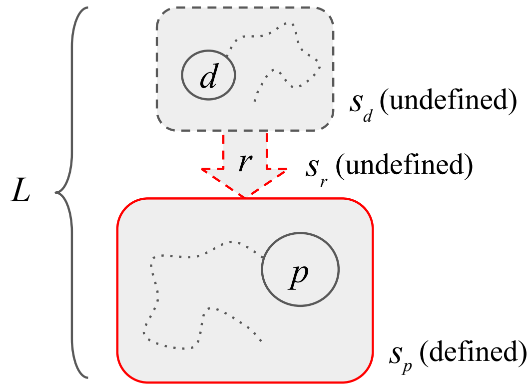

Figure 1: League of Legends L and the subsystems of game developers d and players p. The state space of p (s_p) is constrained by r. Both d and p evolve in their respective state spaces over time.

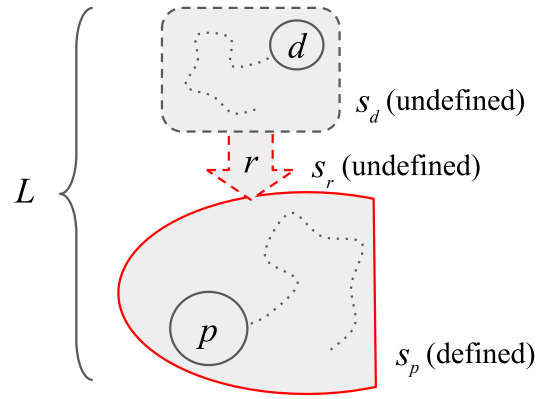

Figure 2: After a week or two, the game developers d will change r, which in turn changes s_p. The players p are able to explore new trajectories within s_p under these new constraints. Under r, s_p is defined, while all other state spaces are undefined due to external factors.

mately a million opponents in any single match, a player must use generally select better strategies. This suggests they must have some understanding of which strategies will beat other strategies, similar to a social aggression hierarchy. Social aggression hierarchies have been well-studied in several species, such as primates, fish, parakeets, and insects(Hobson and DeDeo, 2015). In many of these species, the behavior of individuals is influenced by the overall aggression hierarchy structure as well as their individual awareness of it(Hobson and DeDeo, 2015). In League of Legends, players interact to form a directed network of strategies, which is functionally analogous to a social aggression hierarchy with strategies as nodes instead of individuals. This network is dynamic and strongly dependent on the games current rules, which are minimally changed by the games developer every two weeks.

The system of players, game rules, and game developers may be an open-ended system since its development is driven by human innovation and creativityTaylor et al. (2016); Banzhaf et al. (2016). However, this is difficult to determine quantifiably since the timescale of evolution is much shorter when compared to biological evolution. Though the system as a whole is partly driven by external technological and social changes, it can be approximated as a closed system that evolves under a cyclic dynamic. The system L be partitioned into two interacting subsystems: The players p and the game developers d. These two subsystems evolve throughout their respective state spaces (s_p and d_p) under the constraints of game rules r, where r is changed every week or two. Both subsystems influence the other's behavior much like two biological species interact in a highly non-linear way. The dynamics of L and its subsystems are shown in a cartoon representation in Figures 1 and 2 before and after r is changed by the game developers.

The system as a whole (L) does not evolve under a predefined state space, which is a subtle, yet crucial point. In most mathematical models, state space is almost always predefined and given the correct descriptive phase space, the system can be tracked within a mapped space that is defined (even infinitely)Longo and Perret (2017). However, in the case of League of Legends, the state space of the entire system (s_L) cannot be pre-defined due to external technological and social changes. This is also true of the state space of the game rules (s_r), which is in part determined by the game developers' creativity and access to technology. In the time between events when the game developers changes the game rules r, the players have access to a state space s_p that *can* be pre-defined, albeit short-lasting while the rules are constant. It can be assumed that within this time, players search and find strategies that are likely to win the most matches. By changing the constraints on s_p via r, this allows the player subsystem p to generate dynamics within s_p that do not repeat, thus allowing the possibility of some form of open-ended evolutionAdams et al. (2017). Not that League of Legends cannot exhibit open-ended evolution as a whole system, but within its subsystem.

Since p has the possibility of having open-ended dynamics within an open-ended system L, while evolving under a state space s_p that is predefined under a constant r, it is easier to study under well-known mathematical assumptions. For this purpose, this will be the main focus of this project: **Given a constant r, how does p evolve through s_p within L?**

Dynamics of Strategy Selection

How can a state of s_p be represented? Many players are interested in using strategies that are successful, so it is feasible to capture s_p in terms of strategies that players are using[1]. To better understand how certain strategies become successful via player-to-player interactions under a constant r, I focus on the relationship between the overall strategy interaction network N and an individual players observation of the network n. Though this is not a gauge on the dynamic relationship between L and p, it is a rough model of how p evolves in time under its own internal mechanisms.

In a single match, a player is required to select a single in-game champion (or character) that cannot be changed during the match. Only the most popular match type is analyzed, such that in a single match of ten players, only ten unique champions are used. For simplicity, I assume that a strategy is coarse-grained to the champion that a player selects. Since there are 140 champions in the data set, players have 140 strategies to choose from. Only data from the top 3000 (approximately) skilled players on the North American server are selected, in order to remove noise from lack of skill. This better ensures that match results are driven by strategy selection rather than unevenly-matched team skills. For this analysis, I collected data for all relevant matches that meet this criteria between two game rules revisions, 21 March 2018 and 4 April 2018.

The overall strategy network was constructed in the following way: When one team beats the other team in a match, it is assumed all strategies (champions) on the winning team beat those on the losing team, for the sake of simplicity. This results in a directed graph, where strategies are nodes and an edge from $a \to b$ indicates strategy a beat strategy b. N is just the summation of these edges onto the same node set of 140 strategies. Edge weights are the sum of individual instances (number of times a beat b in the data) and include both edge direction if both edges have a non-zero weight. A players observed strategy network n is determined in the same manner as N, except using only matches that player has participated in, rather than all matches.

Do players win more often if their network n is consistent with the overall network N? Players who have an accurate representation of N may be able to select better strategies to win more matches. To compare each n with N, it is most useful to use pagerank values of nodes, since it can be interpreted as a node's "power" in a dominance hierarchy. This way, the difference between n and N is roughly estimated as

$$\Delta = \frac{\sum_i^{x_n} \mid \text{pagerank}(a_i)_n - \text{pagerank}(a_i)_N \mid}{x_n} \tag{1}$$

where x_n is the number of nodes in n with a non-zero degree. In other words, this is the average difference in node pagerank between n and N. To ensure each n was of comparable size, players who had less than ten matches in the dataset were discarded.

[1]Of course, there are several ways to capture s_p, including player population, skill distribution over time, etc.

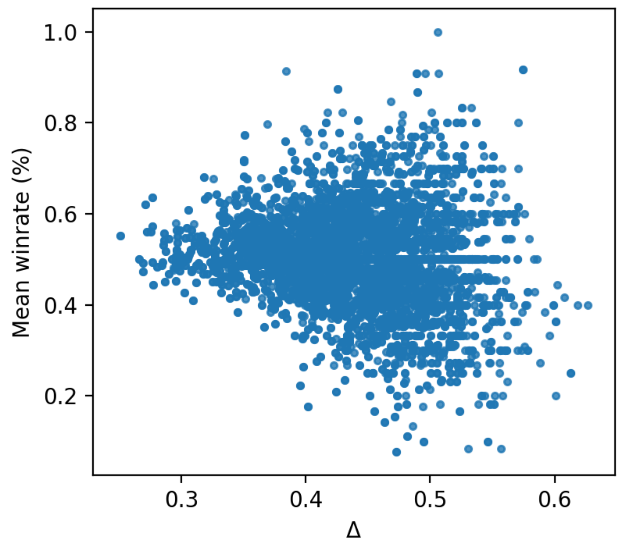

Figure 3: The similarity between individual player strategy networks n and the over strategy network N vs. player mean winrate. Each point represents a single player's point of data, with approximately 3000 players in total.

From Figure 3, players can introduce innovation by playing less popular strategies than the norm. This introduces much more variation in the success of those strategies. However, sticking with one particular strategy does not directly influence an individual player's winrate.

Individuals vs. the Whole

In League of Legends, players are not constrained to playing any particular champion, as long as that champion isn't first picked by the other team[2]. Some players prefer to play one champion as much as possible, while others will pick champions based on what both teams have already picked, since the champion picking process is turn-based by player. Logically, if a player's goal is to win as many matches as possible, they would want to use the best possible strategy by picking the "best" champion under the current r. If players are mainly playing a single champion, do they increase their odds of winning matches? Conversely, does choosing several different strategies increase their odds of winning to account for the wide variety of opposing strategies they might face?

[2]With the exception that each player is allowed to "ban" one champion from the match before each team picks their champions. Banned champions are not selectable by either team. This behavior was ignored for this analysis.

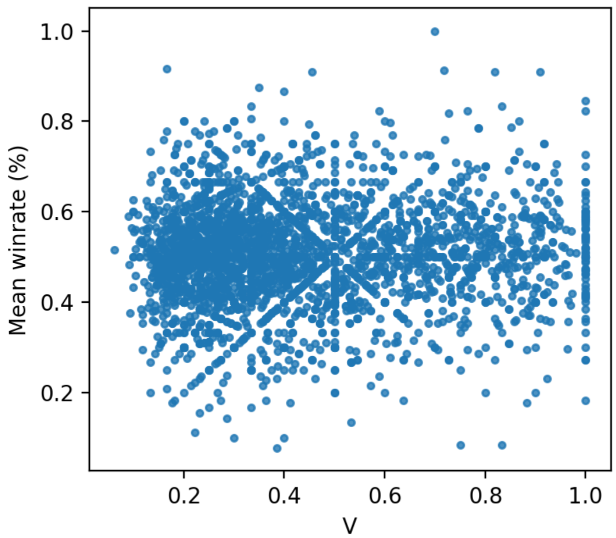

Figure 4: The variability of a player's champion pool V vs. player mean winrate. Each point represents a single player's point of data, with approximately 3000 players in total.

A rough variation calculation for champion selection of a single player is defined by

$$V = \frac{\#\text{matches with player's most played champion}}{\#\text{total matches}} \tag{2}$$

for the match history of a single player in the data set.

From Figure 4, there is no clear relationship between how often a player plays a single champion and the player's overall winrate.

Given a particular r, there is no reason to presuppose any optimal strategy set (here, s_p) exists. It is ambiguous whether or not the game developers change r with an exact knowledge of how it will change the trajectory of p through the players state space s_p. Thus, players search s_p for optimal strategies and it is unclear whether these optimal strategies exist or not. This is why the overall player dynamics is so crucial to how individuals pick strategies, since they rely on observations from their own experiences and those in the same matches. How do the dynamics of the entire player population affect the decisions of individuals? Are players with a more accurate representation of the overall player dynamics (Δ) more likely to switch strategies often or stick with a single strategy?

Figure 5 suggests there may be a weak relationship between players who pick several different strategies over time and their ability to accurately sample the overall strategy network N.

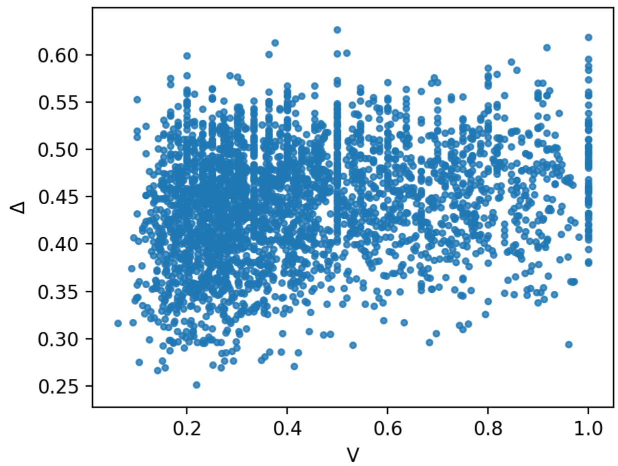

Figure 5: The variability of a player's champion pool V vs. The similarity between individual player strategy networks n and the over strategy network Δ. Each point represents a single player's point of data, with approximately 3000 players in total.

Conclusion

It is unclear whether this analysis has helped determine how novel strategies emerge over time. In fact, it is still unclear how to determine if the system is demonstrating open-evolution because of its short time scales. Big data is providing us with a unique opportunity to study biological systems on a social level, which in turn allows us to possibly identify real-world mechanisms of open-ended evolution. This may be a more powerful and enlightening route to understanding open-endedness (and thus living systems in general) than computational models, but only if we are able to demonstrate these systems have open-ended properties in the first place.

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