Problem Solving Behavior and Information Gathering in StarCraft 2

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Introduction

Complex and creative problem solving is critical for almost any successful human endeavor. Problem solving skills are necessary for a wide range of occupations – such as scientists, doctors, public policy makers, and more – but are also necessary for activities such as cooking, home improvement projects, sports, and board games. Furthermore, it seems intuitive that the effectiveness of problem-solving strategies will increase with experience and expertise. In this project, we seek to study problem solving behaviors and human decision making with the aid of computers and technology.

An increased level of knowledge about this facet of human behavior can help us understand how one achieves expert status in their field. Important aspects of this include the time span needed to develop proper skills, and the level at which efficiency of problem-solving strategies increase with expertise – or the expertise threshold that is needed for an equal efficiency threshold. This knowledge, while not immediately transferable across fields, can inform important decisions about the levels of training needed for professions such as surgeons, pilots, engineers and more. In high-stakes professions such as these, effective problem-solving strategies are crucial because of their ability to affect many human lives.

In studying these problem-solving behaviors and their efficiencies, choosing the right data and domain is essential. We have chosen the real-time strategy game StarCraft 2 – where players harvest resources, build up armies, and seek to conquer their opponent and gain control of the game board or map. In StarCraft 2, players constantly navigate simultaneous and conflicting demands of building their economy versus military expansion, all with incomplete information about their opponent. Additionally, the game is non-turn based, so players make decisions in real-time and can act independently of their adversary. StarCraft 2 is played on 7 different levels of expertise, or ranks, which includes a professional league. This indicates that there is a large range of expertise among the pool of players worldwide. All these factors make StarCraft 2 an exciting realm to study domain-specific problem-solving strategies and their relationships with expertise.

Our results, while not surprising, confirm the relationship between expertise and problem-solving strategies. We took a deep dive into one specific behavior – information gathering of their opponent – and found that expert players exhibited that behavior far more frequently than novice players. We also found that expert players use this behavior in a more strategic manner, which will be explored later in this paper. These results are very foundational and can be used as a stepping stone for future important work.

Related Work

Previous research on StarCraft 2 has identified many important features of player behavior and strategies that contribute to success, or winning matches, as well as which ones differentiate experts from novices. From the winner prediction models produced by Ravari, Bakkes, and Spronk [2] and Erickson and Buro [1], we know that characterizing commands and behaviors as economically motivated or militaristically motivated is an important distinction. Ravari, Bakkes, and Spronck [2] found that the most influential features for success were income, defined as resources collected over time, control, defined as a category of commands issued, economic commands, unspent resources, and the difference in economic value for each player's bases. Despite the fact that most of these factors are economically centered, they concluded that while a player's economy is critical to game success, the strategic aspects of a player's game behavior is more important overall. The work done by Erickson and Buro [1] has similar relevant findings: features including economy, military, economic skill, militaristic skill, and map coverage are all significant in predicting the success of players across the board. These results encourage future work to explore the strategic decisions that players make in StarCraft 2 in congruence with their economic gameplay. Additionally, a more nuanced understanding of strategic behavior would emerge from the combination of other smaller behaviors.

Furthermore, the work completed by Thompson et al. in 2013 [4] and Yan, Huang, and Cheung [5] in 2015 both provide a detailed look at how expert players differ from novice players. Thompson et al. identified 12 different markers of expertise, each of which vary in their importance per player rank. The most prominent ones included Actions per Minute, Hotkey selection rates, and other features that fall under the umbrella category of Perception Action Cycles (explored in depth by Thompson et al. in 2017 [3]). This work provides analysis of quantitative metrics that require little to no interpretation. While these features are clearly significant in distinguishing experts from novices, our work provides analysis on a qualitative strategic behavior that arguably encompasses many of these significant quantitative features. We seek to build upon the complex understanding of expertise initially formed by Thompson et al.

Similar to our goals, Yan, Huang, and Cheung [5] analyze the patterns of control group selection rates. Control group selection is a behavior that players use to quickly access groups of units that they previously assigned to a specific key. Control groups, or hotkeys, allow players to execute commands at a much higher rate of speed and efficiency. Yan, Huang, and Cheung [5] analyze control group selection rates in peacetime versus battle time, as well as make distinctions for what kinds of units are in the groups being selected. Their work provides an in-depth, graphical analysis of how expert players differ from novice players. In their conclusion, they emphasize the perceived relationship between expertise and habits, noting that they are mutually reinforcing – experts seem to have high performance because of their habits, and their habits appear to exist as a result of consistent high performance. This analysis provides intriguing insight into the relationship between creative problem-solving strategies and expertise.

We seek to expand on the nuanced picture of expertise by looking in depth at information gathering as a strategy – known in the StarCraft 2 community as scouting. Scouting can provide a player with more complete information about the game map, as well as their adversary. They may learn things such as where their opponent's bases are located, the strength of their opponent's army, choke points and potentially successful attack points, potential expansion locations, and more. On the other hand, scouting requires a player's time and attention and could possibly result in the loss of army units. We follow in the steps of Yan, Huang, and Cheung to provide a graphical analysis of scouting behavior throughout the levels of expertise.

Methodology

One major advantage of using StarCraft 2 as our domain is the data collection process. The game automatically produces a replay file for each match, which contains every command issued and event that occurred for each player throughout the entirety of the game. This means that the matches used in our dataset occurred in normal circumstances for each player, eliminating the detrimental effects of players completing tasks in a laboratory setting. We obtained our replays from gggreplays.com and lotv.spawningtool.com, which are both websites where players upload their replay files and are given a thorough analysis of the game events. These websites are commonly used by players that are seeking to learn more about the game and to improve their strategies. Because of the function of these websites and the volunteer status of their users, it is important to note that our dataset has probable selection bias. We also implemented some data quality control and excluded games that were not played between two human players, were shorter than 5 minutes in length, or replay files that had no information about the winner.

For our analysis, we continued using the notion of expertise in this context as originally defined by Thompson et al. in 2013 [4], where the seven ranks defined by StarCraft 2 are split into three levels of expertise. Because the adjacent ranks are mostly indistinguishable from one another, the levels of expertise remove ranks on the bordering edges. As a result, the novice category is comprised of Bronze – Silver players (numeric ranks 1 and 2), the proficient category is comprised of Platinum – Diamond players (numeric ranks 4 and 5), and the expert category is comprised of only the Grandmaster, or professional, players (numeric rank 7). In total, our dataset contained 46,968 replay files, each of which has data on two human players. The total number of unique players in our dataset is 29,308. The breakdown of unique players by expertise is as follows – Novice: 3,509 (Bronze: 439, Silver: 3,070), Proficient: 18,491 (Platinum: 8,598, Diamond: 9,893), Expert: 334. The dataset also included 4,978 Gold-ranked players and 1,996 Master-ranked players, which were removed for analysis on expertise levels.

Each replay file contains extensive game data such as when each unit is spawned, unit positions, when each unit dies, which part of the map each player is viewing at each frame, commands issued, and more. We used a 3rd party python module – sc2reader – to process each replay file and convert them to an accessible format. From there, we used python to parse through the data and detect larger game events such as battles and scouting. For each game, we assume that neither player gives up or deviates from their typical strategy, each player's rank is correct, and the processed data is accurate.

The following is a description of thresholds and decisions we made in identifying various game events. Battles are defined as conflicts between players in which greater than 10% of either player's combined army value and economic value is destroyed. In order for unit deaths to be considered part of the same conflict, they must happen within 160 frames of one another, or about 7 seconds. Another common strategy for StarCraft 2 players is to harass their opponent, which usually consists of sending a small number of troops to their opponent's base with the intention to destroy workers, which are units that harvest resources. This strategy is intended to slow the opponent's economic growth, while also demanding their attention. Conflicts that do not reach the 10% threshold for battles, have a small number of units destroyed, but at least 50% of the units destroyed were workers, are labeled as instances of harassing. We defined scouting as a behavior that occurs when a player is viewing their opponent's base (the location of their camera is within 25 units of a base location), has at least one military unit within 25 units of their point of view, but is not engaged in battle or any instance of harassing. For reference, a typical game map is a grid of about 200 units by 200 units. We also added a 20 second buffer on either side of each battle and instance of harassing in order to avoid false-positive labels of scouting.

Once we had defined and identified scouting, we decided on a few metrics to analyze each player's scouting behavior. Of these, the most prominent results in distinguishing experts from novices came from the following: investigating a player's frequency of scouting, looking at which times during the game players were scouting, categorizing players based on their consistency of scouting, determining if the player did an initial round of scouting, whether or not a player consistently scouts new areas of the map, and whether or not a player consistently scouts between battles. Finally, we used the ggplot package in R to produce our graphical results.

Results

In this section, we will present the results of our analysis and demonstrate how scouting behaviors are closely tied to expertise. Figure 1 explores the relationship between the frequency of scouting for players and their rank. As is evident from the boxplots, the lower ranks are mostly indistinguishable from one another, as observed by the median, while we see a great increase of scouting frequency in the higher, professional level ranks. It is clear that more experienced players implement scouting more frequently throughout the game, which leads us to believe that scouting is an effective strategy.

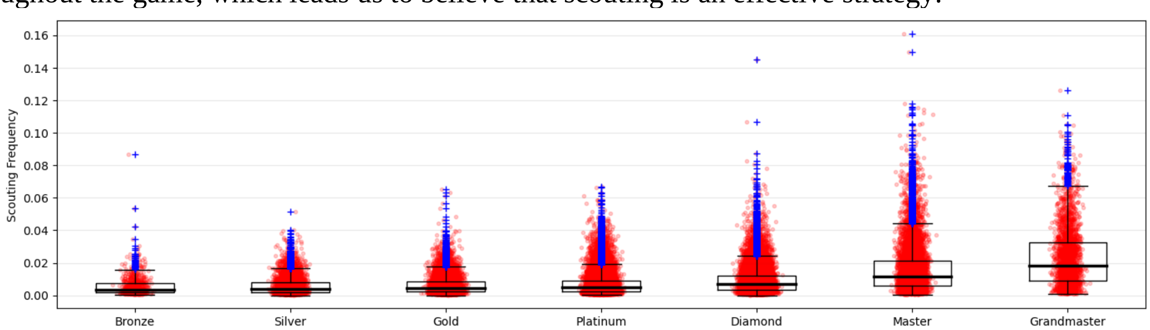

Figure 1. Boxplots of the Scouting Frequency for each player at each Rank. Rank is on the x-axis and increases to the right. Scouting frequency, defined as the number of instances of scouting per second, is on the y-axis. Graph produced by data_diagnosis.py.

Furthermore, Figure 2 displays at which points during the game players are scouting. Novice players are consistent in their scouting throughout the game, with a small percentage of matches with scouting at each point (no more than 20%). Proficient players show slightly more scouting behavior towards the beginning stages of the game compared to the middle and end, but still have relatively low percentages of matches (no more than 30%) where scouting occurs at each time. Expert players, on the other hand, are clearly distinct from novice and proficient players in the percentage of matches where scouting occurs (nearly 100%), but also in their tendencies to scout much more in the beginning of each game. This demonstrates the perceived importance of gathering information about the map and the adversary early in the game to inform strategy and military decisions. One assumption we make is that gathering information in the mid to late stages of the game might be too late to make any real changes in one's strategy – revealing the necessity for early game scouting. Perhaps novice players are aware that scouting is an important factor of the game, but do not have enough experience to execute it properly or respond in an effective manner.

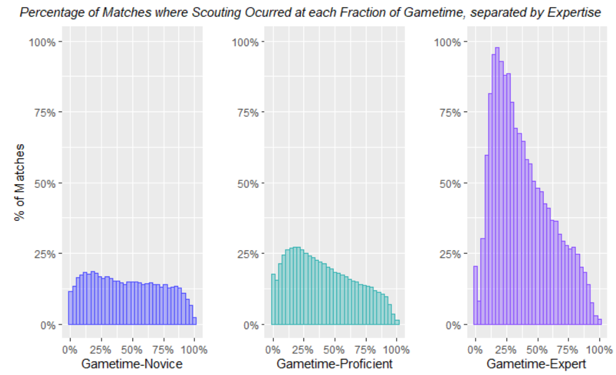

Figure 2. Displays when players at different levels of expertise are scouting. For each histogram, the x-axis is time as a percentage of the total length of each game. The y-axis is a count of how many players are scouting, as a percentage of the total number of

Lastly, Figures 3, 4, and 5 demonstrate how scouting can be employed strategically, and the differences between novices and experts in that regard. We hypothesized that players with greater control and intentionality with their scouting behavior would have more success implementing these strategies. We also assume that these strategies would reveal a deeper level of knowledge about their opponent and the map than if a player were to fail to do these things.

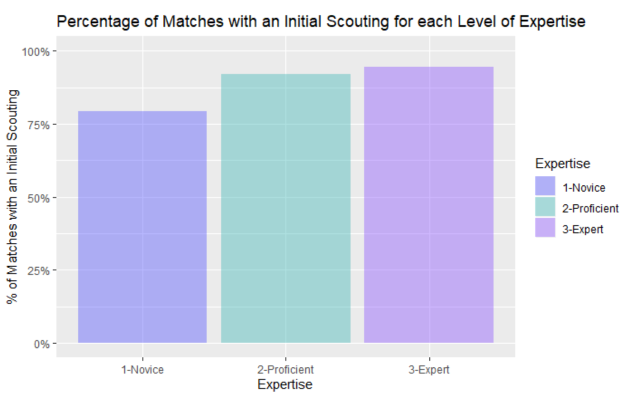

Figure 3. Bar graphs of the percentage of players that exhibit an initial scouting for each level of expertise. A player has an instance of initial scouting if they scout in the first 25% of the game. On the x-axis is each level of expertise, and on the y-axis is the count as a percentage of the number of matches at each level of expertise. Graph produced by ScoutingAnalysis.Rmd.

We explored three metrics of potentially useful strategic implementations of scouting. A) Whether or not a player executes an instance of scouting in the first 25% of the game. Figure 3 reveals that 17% more of expert matches have an initial scouting than novice matches. B) Whether or not a player consistently scouts new areas of the map. Figure 4 reveals that 27% more of expert matches have players that consistently scout new areas than novice matches. C) Whether or not a player consistently scouts in between battles. Figure 5 reveals that 4% more of expert matches have players that consistently scout between battles.

Our graphical analysis reveals that experts do, in fact, implement all three of these strategies more often than novices, confirming that players with higher levels of expertise are more adept at using scouting in a strategic manner. However, not all of them appear to be as common as an initial scouting. This warrants further investigation into the tangible advantages of these metrics.

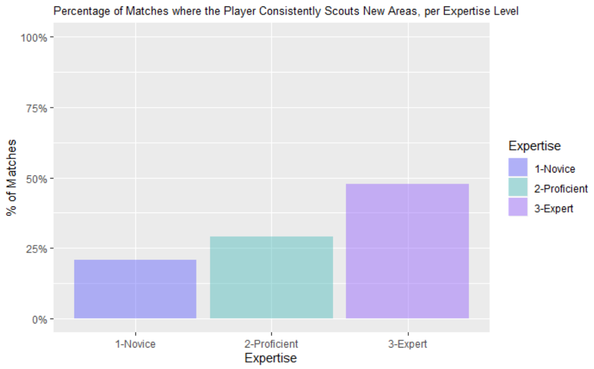

Figure 4. Bar graphs of the percentage of players that consistently scout new areas of the map for each level of expertise. A player's scouting behavior is considered as consistently scouting new areas if the average distance between each area they scout is greater than or equal to 20 units. A typical sized map is around 200 by 200 units. On the x-axis is each level of expertise, and on the y-axis is the count as a percentage of the number of matches at each level of expertise. Graph produced by ScoutingAnalysis.Rmd.

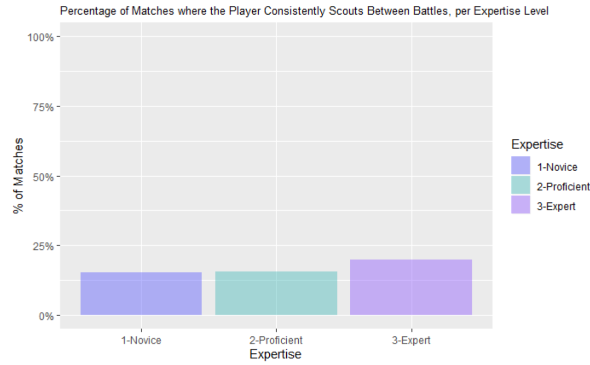

Figure 5. Bar graphs of the percentage of players that consistently scout between battles for each level of expertise. A player is considered to scout consistently between battles if at least one instance of scouting is observed for 70% or more of the peacetime periods between battles. On the x-axis is each level of expertise, and on the y-axis is the count as a percentage of the number of matches at each level of expertise. Graph produced by ScoutingAnalysis.Rmd.

Overall, the primary conclusions of our work is that the strategy of information gathering, known as scouting, is undeniably intertwined with expertise. Not only do expert players scout their opponents more frequently and more often in the early stages of a game, they also employ a more calculated approach to scouting. This means more intentionality in what information they are gathering about their opponent – from what their early game military looks like, where they have expanded to build new bases, and how their military has changed between each battle. These results prove that players develop skills and problem-solving strategies that turn into adeptly wielded habits as they climb through the ranks of expertise.

Discussion and Future Research

Our results have expanded upon our understanding of expertise in relation to problem-solving strategies and effectiveness. As we learned from Thompson et al. in 2013 [4], experts have higher frequencies of lower-level tasks, such as actions per minute and their perception-action cycles. From our work, we learned that players combine these tasks to execute more complicated strategies such as scouting, and experts exhibit these qualities at much higher rates as well. Not only do experts consistently scout more than novices, but they also have a higher level of executing scouting in a very strategic manner. These results confirm our intuition that problem-solving strategies are implemented more frequently, and more effectively, when done by experts. However, this is an observational study, so no causal relationships can be assumed. Nevertheless, our results have a few important implications as well as room to grow in the future.

In relation to our question posed about the time it takes to become an expert and the expert/efficiency threshold for problem-solving strategies, our analysis provides important insight. We propose that the paths to these thresholds do not increase linearly with time and experience. We gather this from Figure 1 and Figure 2, which both display how the frequency of scouting and when scouting occurs during the game changes through the levels of expertise. However, these changes are clearly non-linear and perhaps even exponential. This aspect of how expertise is related to problem-solving strategies appears to be important to understand the shape of a learning curve for any specific domain. Further exploration into this observation would be an interesting line of future work.

Additionally, our analysis is limited in its ability to understand the tangible advantages of scouting and whether scouting does indeed contribute to the success of a player. It would be valuable to understand exactly what players are learning each time they complete a cycle of scouting, and what exactly players are doing with this information. As stated before, we assume that players learn information about where their opponent is located and the strength of their opponent's army, among other things. We also assume that in response to scouting, higher level players will make adjustments in their larger strategy based upon what they learn. This could include focusing on their economy and expansion, building a different kind of military, or launching an attack. Lastly, we assume that if players are able to learn about their opponent and respond in an effective manner, that this will increase their chances of success. A future exploration into all of these assumptions would provide valuable information for analyzing the strategic behavior of players in StarCraft 2.

References

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