Starcraft II: Leaguing Up and Anti-Smurf Detection

A report by Jake Getz

Introduction

By all accounts, achieving a high league in Starcraft 2 online play is hard. In fact players spend months, if not years, wobbling up and down within their league, struggling to break into the next tier. This process is hard enough that it has spawned and supports an entire online infrastructure around strategy guides, coaching, and tips & tricks all targeted at helping players “rank up”.

Problem Statement

This project’s aims are twofold. Firstly, to analyse gameplay data of players across all of the leagues to determine which features most effectively lead to ranking up. Secondly, to help Blizzard, the company who makes Starcraft 2, detect players who are “Smurfing”. “Smurfing” is when a player who is high rank makes a new account and intentionally plays in a league well below their skill level. This creates an unbalanced and frustrating play experience for lower league players.

The Data

“SkillCraft1 Dataset”

Mark Blair, Joe Thompson, Andrew Henrey, and Bill Chen from the UCI Machine Learning Repository

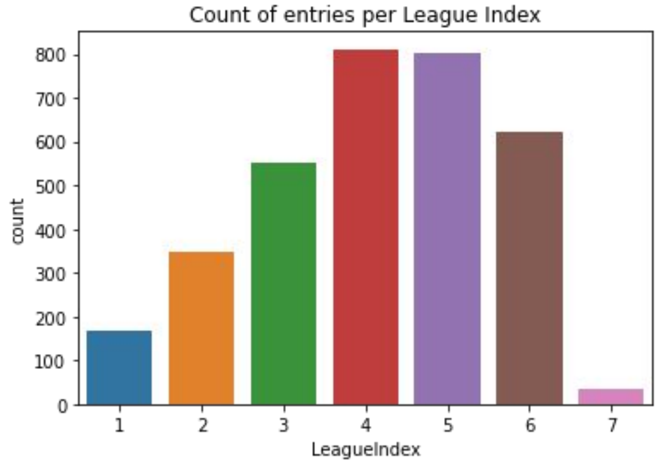
Over 3300 Games

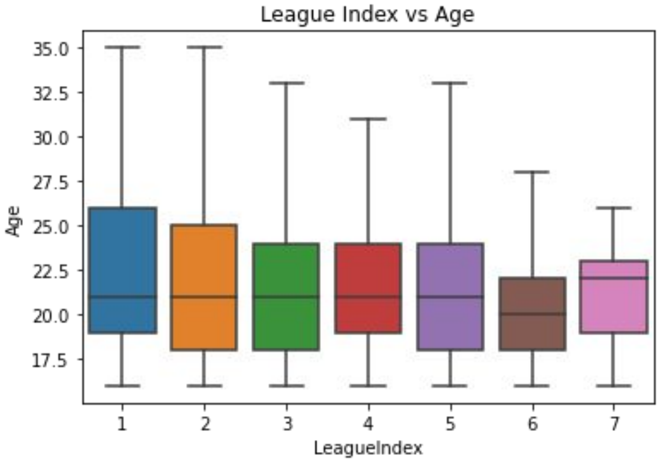
- Varying Leagues
- Wide range of ages and hours played
- Win agnostic

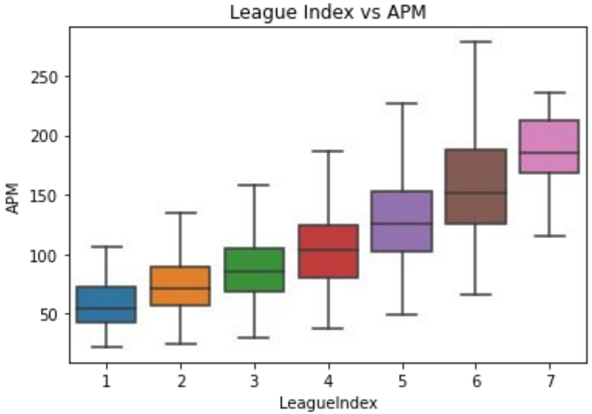
Data Distribution

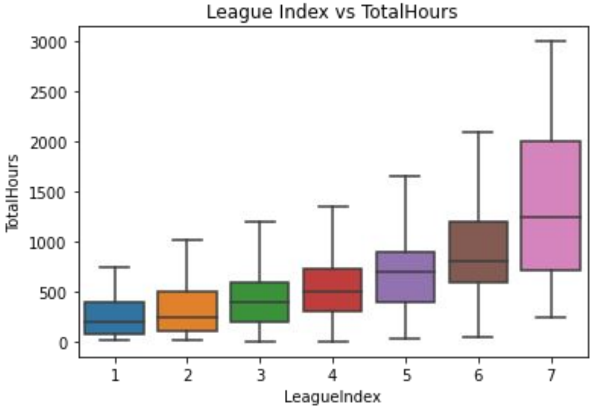
We can see that the majority of our data is focused in leagues 2-6 therefore analysis about players in league 1, and especially in league 7 may be less trustworthy.

We also notice that the majority of our data comes from players of the same age group, our only “uncontrollable” feature. Clearly age is not an indicator of league index.









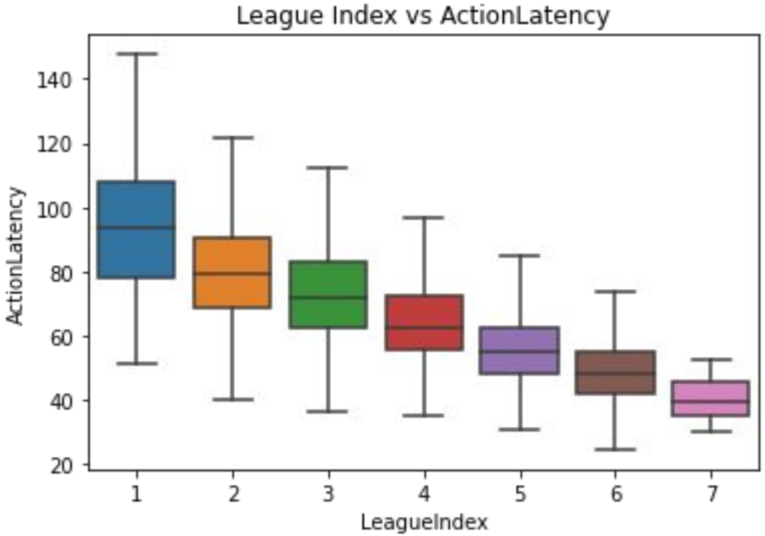
Exploratory Trends

A high APM correlates with a high League Index across our entire data set, we have very few entries with a low APM but high League Index. We will see later if this is confirmed for individual League Transitions.

Unlike APM, while a larger number of total hours does seem to increase general league index, there are plenty of players with lower numbers in high leagues and visa versa.

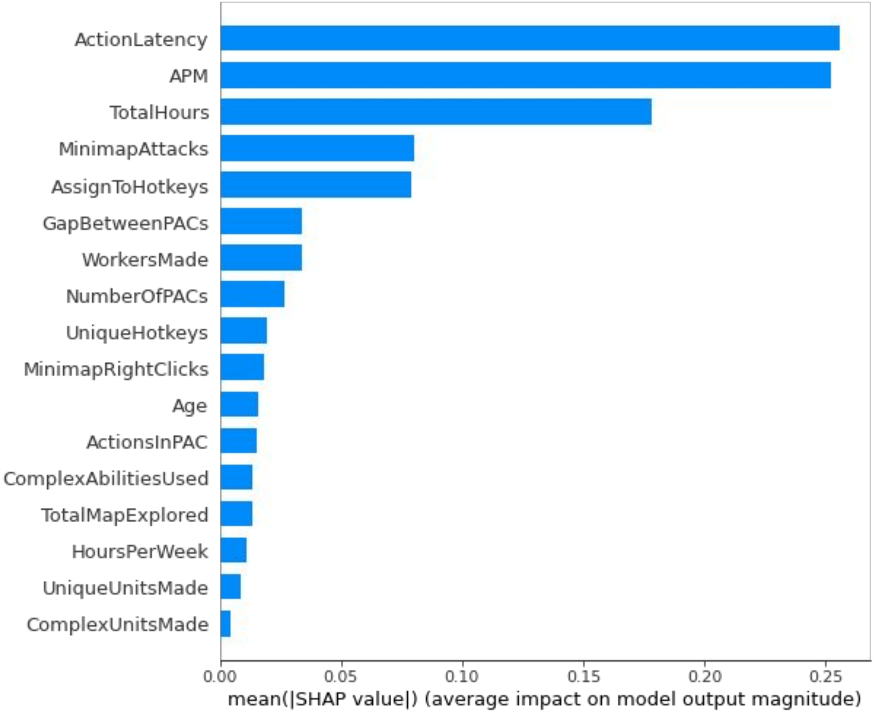
Action Latency

Action Latency is our measure of how long it takes to perform the first action after a shift in focus. Rather than APM, which counts the pure volume of actions and can sometimes be impacted by things like physical dexterity, Action Latency instead measures how long it takes to see the new information and take some action in that new space. We see tight bars on our graph in a steep descend as league increases, meaning players with low action latency aren't in low leagues.



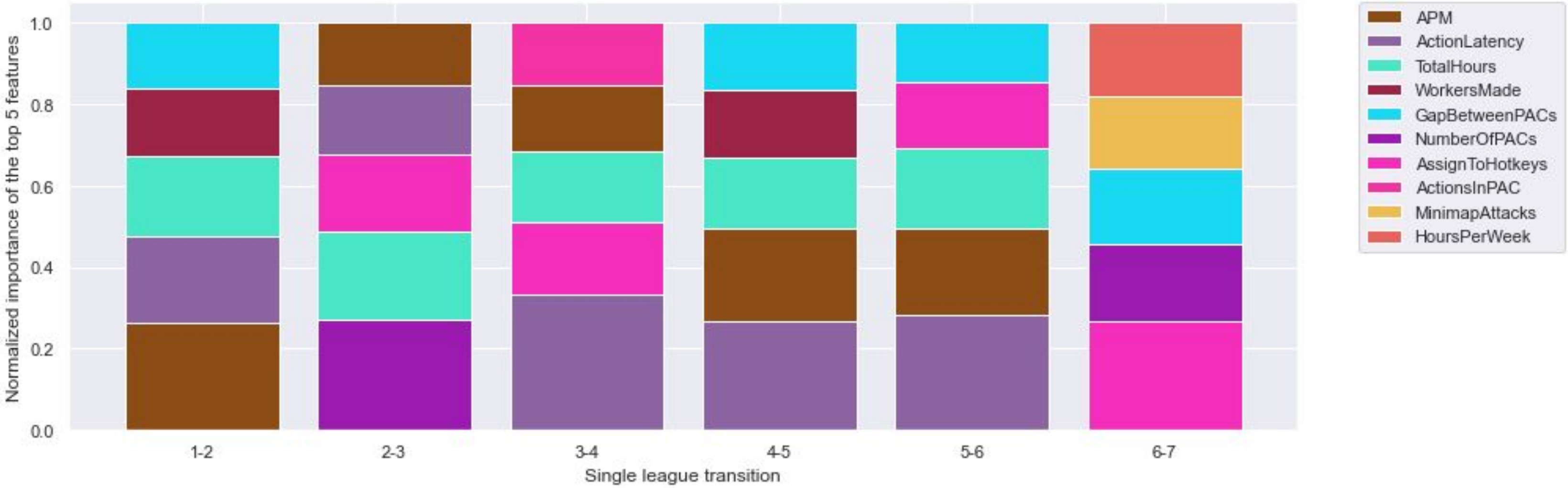
Full Set Feature Importance

We analyzed the feature importance for the entire data set and sanity checked our results with the SHAP method. As suspected from our exploratory analysis, Action Latency and APM are both solid features to focus on for achieving a high league with total hours in a close but clear third place. This is useful as general oversight, but for a player in a specific league we were interested in what specifics would get them from their league to the next.



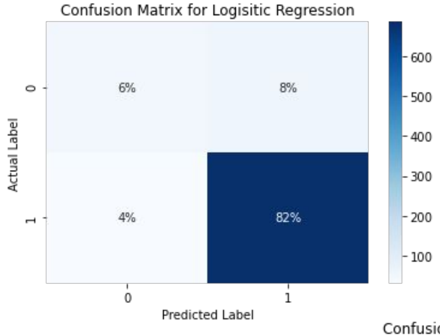
League Transition Importances

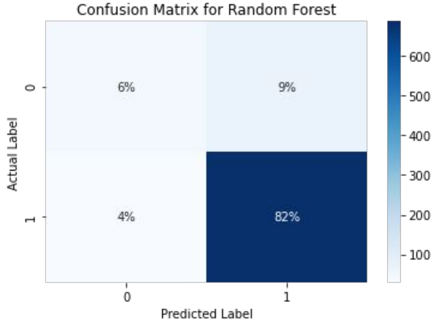
We broke down each league transition into is 5 most important features and found that Action Latency, APM, and Total hours showed up the most consistently across our transitions. Of note, due to the few entries we had concerning league 7, the 6-7 transition is not the most trustworthy transition data.

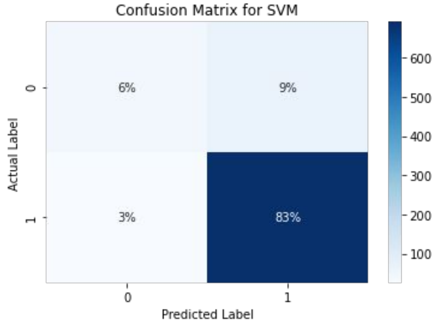


Anti-Smurf Detection

As mentioned before, smurfing, the process of intentionally playing in a league below your skill level, creates a bad experience for players who are playing in their correct league. We operate under the assumption that Blizzard wants to ban smurfers and is relying on our machine learning model to take the game data we receive and predict the players true league index. If we predict them in a high league index, index 3 or greater, and they are in a low league index, 1 or 2, we assume they are smurfing and ban them. We implemented 3 models, Logistic Regression, Random Forest, and SVM, to decide which model is best. We know predicting someone as high league, category 1, when they are actually low league, category 0, is our worst case so we move forward with logistic regression

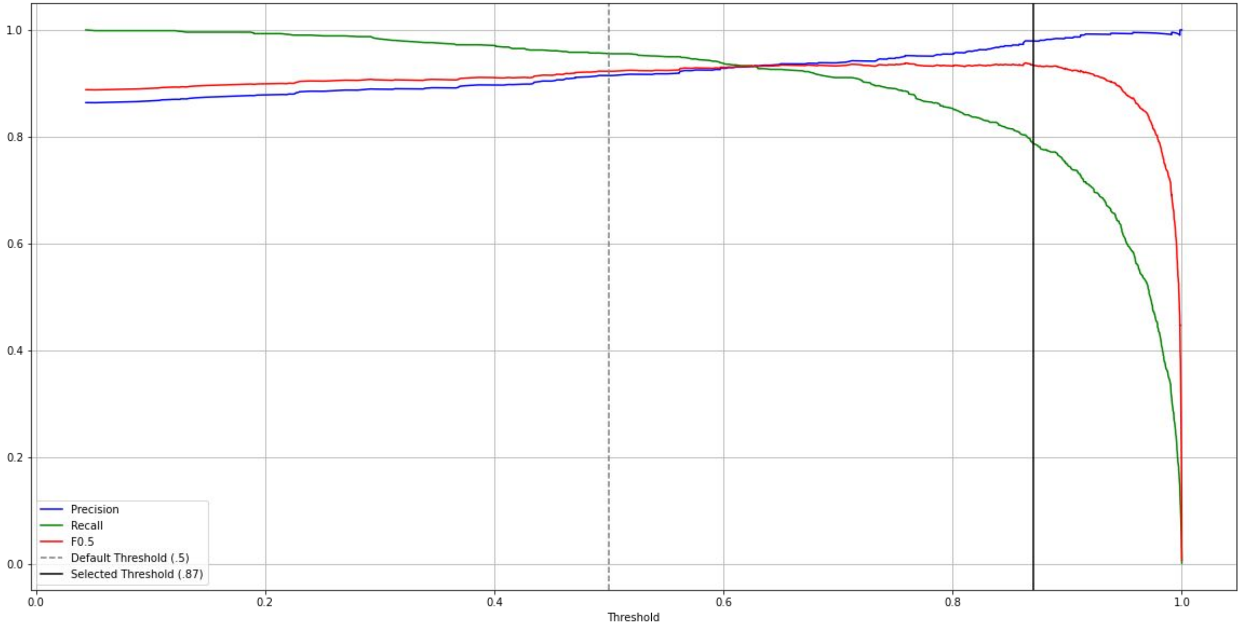


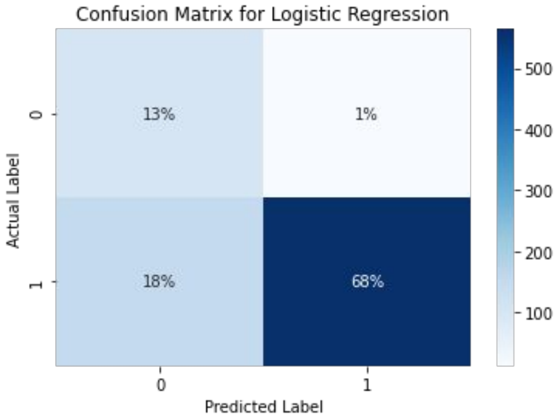




Thresholding

Clearly incorrectly banning 8% of Starcraft 2 players in unacceptable, so we select a threshold for our model which precision over recall without abandoning our F0.5 score. For our model that’s a threshold of .89





	Precision	Recall	F1 Score	Support
Low League	.41	.90	.56	118
High League	.98	.79	.87	717
Total	.90	.80	.83	835

Post Thresholding

After thresholding at .89, we have a model that only mis-labels 1% of players who are in low leagues as in high leagues. While this model does error on the side of letting some smurfers through, a high precision on the High League and a high recall on the Low League means this error will be as minimal as possible while still correctly labeling over half the high league players.

Conclusion

- We found that maintaining a low Action Latency frequently plays a large role in increasing league index, specifically in the middle leagues, where the majority of the player base tends to clump. We also found that until the absolute highest of leagues, total hours spent on the game are a pretty solid indicator of success, and that if you are stuck in a lower league, simply playing more tends to be an effective way of increasing your league index.
- We simulated “Smurf” detection, looking for players creating new accounts to play at low leagues disproportionate to their skill level. We thresholded our predictive model to protect against incorrect smurf labeling and found a model that tends to catch players in low leagues playing well above the average skill level of those others in their league. We chose a conservative model, operating under the assumption that Blizzard would ban offending players which makes the “cost” of being wrong particularly high.

References

1. UCI Machine Learning Repository: Skillcraft1 master table dataset data set,

   https://archive.ics.uci.edu/ml/datasets/skillcraft1+master+table+dataset Accessed December 8, 2021