EXPLAINABLE AND BETTER ALGORITHMS FOR INDIVIDUAL AND TEAM GAMEPLAY MODELING, AND THE POSSIBILITY OF A NEW FEATURE ON STEAM FOR DOTA 2

1. SUCCINCT STUDY OF PERTINENT ACHIEVEMENTS

This section briefly, although precisely, describes the feature selection and algorithm selection (with pitfalls) for hero pick, functionality classification, in-game player behavioral analysis, and correlation of these with game outcome. I have specifically chosen a set of studies that have achieved a fair accuracy on their prediction, and that have for most part used supervised or explainable unsupervised artificial intelligence to model the information.

The reason for constraining the study to explainable algorithms in context of the DotA2 game physics and player expertise, is directly related to the feasibility of creating an intelligent feature that offers personalized and in-depth feedback to players at all skill-levels, in terms of atomic decisions taken and overall strategy, described post-game to them, in natural language. This training would not be possible if the mathematical models that produce accurate predictions, cannot be mapped at intermediate computation stages to actual game events and consequences that can be later explained to the player. For this reason, papers that have achieved their results through the use of neural networks have been restricted due to the lack of explainable intermediate results generated by them.

In this frame of mind, the following is a summary of what has already been researched and evaluated -

A. Game Outcome – High-Level Feature Selection and Algorithm Selection

i. Basis of Study –

1. *Title – Performance of Machine Learning Algorithms in Predicting Game Outcome from Drafts in Dota2*
2. *Authors – Aleksandr Semenov, Peter Romov*
3. *Month and Year of Publication – February 2017*
4. *Access Link - Game Outcome Prediction*

ii. The work accounts for taking inter-hero interactions and using the observations as input to the following algorithms – Naïve Bayes classifier, Logistic regression, Gradient Boosted Decision Trees and Factorization Machines, after which a comparison was performed on the results of each.

iii. As part of the short introduction to the game, it chooses the reference of the function of the player, rather than the choice of hero. It also gives a brief of the total possible combinations heroes, spells, and items, somewhere near 140 million combinations to analyze. This, as clearly seen is a combinatorics problem.

iv. The previous research focusing on game outcome prediction had shortcomings such as lack of accurate methods for inter-player interaction modeling, inconsistent contexts used for data collection, overfitting issues, less focus on result quality in contrast with precision, lack of data, and to some extent, not the best choice of algorithm either.

v. Remediation to the previous points was handled by verifying the context within which the data was being mined (not mixing professional and public games, and taking a duration where no core game mechanics were changed), re-run the older algorithms and store the results, introduce factorization machines algorithm for inter-player interaction modeling, and compare game outcome results.

vi. The data distribution for all different hero picking modes in terms of skill-level show that there are maximum number of Normal- Skilled players followed from far behind by the Very-High-Skilled players followed closely by the High-Skilled players which is the minimum in all modes.

vii. When comparing naïve bayes classification and logistic regression, the key reason the latter was also checked was because it could force symmetry onto the hero capabilities of the radiant and dire teams, however from the results it was found that this extra measure wasn't needed since on the whole, the teams were balanced even without this symmetry being enforced.

viii. Baselining - The naïve bayes assumes class conditional independence as per its definition and computes univariate probability estimates from the training set from previous studies. In these studies, a hero is picked in context of a specific function and the outcome was noted. Then using the Bayesian rule across all the heroes picked, the probability of the game win given the hero set picked is evaluated, and the most probabilistic class is determined. The logistic regression is similar, since it is solely dependent on individual picks. These methods have been used before and served as a baseline for prediction accuracy.

ix. Benchmarking – The factorization machine used here takes the interactions between pairs of heroes and this becomes the dependent for game outcome. Another point to be noted is that this work also covered second order interactions which I assume indicates that a pair is pitted against another pair and the interaction is studied and taken as a dependent for the game. In the pursuit of defining and modeling these minute interactions themselves, a gradient boosting algorithm for decision trees listing these interactions was used. The final binary prediction of outcome (radiant win/dire win) was performed with a simple Bayesian inference computation. It is worth noticing that the second-order model extension allowed here, did not make a significant difference to the results. This was the benchmark, and still is, as far as public results go.

x. The results arrived at, based on the ROC AUC indicating quality as well as accuracy prediction beat the previous algorithms by around 3% with the addition of the new algorithms.

xi. The other results implied that the game pick mode did not affect game outcome (not even the Captain's Draft), that interactions modeling definitely improved quality and accuracy, and the second-order interaction study may have been auto-biased by the decision tree constructed, because gamers in general agree that pair versus pair interactions bear consequences. Also, the distribution of AUC results across skill-level shows that prediction accuracy is lesser for highly skilled heroes, maybe due to their knowledge of picking the right players, having more heroes to pick from, and having greater strategic (interaction) expertise and creativity, than can be handled by the computation in this work.

TO QUOTE FROM THEIR WORK –

"*Such work might be promising and useful for the game developers to access the balance of a game, and for professional teams, because it will allow them to make data-driven decisions for the drafts during the training and preparation for the tournaments.* ***Besides that, building applications based on recommender systems for causal players also looks promising both from a scientific and a commercial point of view.***"

And they're right about that (Refer section 2).

B. Hero Selection

i. Basis of Study –

1. Title – Machine Learning Approaches to Choose Heroes in Dota2

2. Authors – Iuliia Porokhnenko, Pter Polezhaev

3. Month and Year of Publication – April 2019

4. Access Link - IEEE Publication (24th Fruct Conference)

ii. This paper puts a claim to the possibility of predicting the game result based on the hero selection primarily. The part that I have focused on are the hyperparameters used for the linear regression and linear SVM classification models for determining the set of features to look for in a hero that will be of significant consequence while modeling a game.

iii. Similar to the previous study, the outcomes are of two types – radiant win and dire win. The prerequisites are that –

1. Game modes must ensure that each hero has a non-zero probability of getting selected.
2. The skill-level of players must be high. This means that heroes will be picked aptly for the function they will perform and align with the player's strengths. Also, this reduces noise generated by players who have no idea what they're doing or why they have made a decision.
3. The players stay for the whole match.

iv. The following algorithms were used, with the help of readymade libraries, and results were compared –
   1. Gradient Boosting Classification – Key strength is it's exhaustive manner of tackling hero combinations and aiding regression and classification problems.
   2. Random Forest Classification – Build multiple decision trees and aggregating sub-results to boost accuracy.
   3. Logistic Regression – Used for high-dimensional problems that have a binary classification.
   4. Linear Support Vector Classification – Uses only linear core and scales better and learns faster than SVM.
   5. CatBoost Classification – Gradient Boosting on Decision Trees

v. Hyperparameters were manually picked for each of these algorithms for the training for feature selection. This training was performed using GridSearchCV algorithm (ready-made), and the performance classification was validated using k-fold cross validation method.

vi. The ROC AUC was used because the number of instances per class was not the same, and hence the results are based and True Positive Rate and False Positive Rate. The logistic regression and LSVC classification models showed best results of around 77% true positives out of total positives and the former had a better time-complexity than the latter.

vii. This paper may serve as a baseline for keeping tracking that the hero pick, reasoning and relation with the game outcome (at the very least) and player improvement (best case) do not fall below this benchmark.

C. Behavior-Based Player Function Classification

i. Basis of Study –
   1. *Title – Machine Learning Approaches to Choose Heroes in Dota2*
   2. *Authors – Christoph Eggert, Marc Herrlich*
   3. *Month and Year of Publication – December 2015*
   4. *Access Link - Springer link*

ii. Access Link The work investigates the applicability of supervised learning algorithms used for analyzing individual player behavior and determining which commonly accepted and specific function the player has assumed. This is closely related to the next sub-study that analyzes spatio-temporal behavior of players within a team.

iii. The most valuable part of this work is the intent behind it, which doesn't focus on predicting game outcome but rather focuses on assessing the player's decisions irrespective of the gaming outcome. In other words, it focuses on what the player intended to do in fortuitous circumstances rather than on what really happened in the end. This is important in the present context since this kind of modeling perspective is already suitable for player improvement and training methods.

iv. The features are taken from a repository of DotA2 replay files and some of them are not explicitly noted by the API and hence need to be derived. Out of this set, using best first search a subset of features are selected for further classification of players into roles. This subset can roughly be divided into –
   1. Space and Movement
   2. Early Ganks
   3. Team Fights
   4. Support Items
   5. Damage Types

v. For classification of players into roles based on these subsets, logistic regression, SVM + sequential minimum optimization, random forest decision trees, and naïve Bayesian networks, and results were compared. 10-fold cross-validation is applied as usual.

vi. This process is applied to a popular larger set of roles as well as to a reduced set of roles.

vii. The subset of selected features were KDA ratio, last hits, early ganks, number of support items, damage to neutral creeps, damage to regular creeps, lane partners, kills, experience, deaths, team fight participation, early movement (cells visited on the grid), and damage to heroes.

viii. Space and Movement – They are classified by top, mid, and bottom lane. The jungle lane may be used and is considered a roaming area, and has a vague boundary. Solo and partnered lane attributes were added. To account for unnecessary movement and noise, number of grid cells visited is calculated as an attribute.

ix. Early Ganks – Aggressive players that don't stick to their lane and are on roaming increase their early gank attribute goes up by one. There is no hard line to classify early gankers, since false positives needed to be avoided.

x. Team Fights – A fight entry is initiated when 7 players are involved within 20% of the map and undergo damage from within these 7 players. The fight is declared ended when no team makes a move on the other for more than 5 seconds. This uses spatial, temporal, and damage data to pinpoint fight boundaries.

xi. Support Items – This isn't directly available on the replay information, but the count of support information makes one attribute.

xii. Damage Types – This includes damage to heroes, damage to towers, and damage to regular and neutral creeps. And it is done by mining the database that registers instances with identifiers of attacker and victim.

xiii. Misclassification of roles sometime happen when two players in different roles perform the same actions but with different intent (active carry vs ganker/farming carry vs pusher) and this can also happens due to unclear game transitions. Excluding feeder and inactive players, certain players do not or cannot perform the role of a function distinctly enough, and they generate noise in this information. Sometimes, roles change dynamically within the game when needed and this may be solved by taking shorter spans of time, but enough data for such sub-instances is not available.

xiv. Classification of the enlarged set was marked at 75% accuracy, while classification of reduced set was marked at 96% accuracy. Logistic Regression classified the results based on the selected features the best.

xv. Performance noise is a problem that does not occur on full-team analysis, but occurs with individual player analysis, and this is something to take into account while preparing a personalized training module.

D. Tactic Observation

i. Basis of Study –
   1. *Title – Skill-Based Differences in Spatio-Temporal Team Behavior in Defense of the Ancients 2 (DotA 2)*
   2. *Authors – Anders Drachen, Matthew Yancey*
   3. *Month and Year of Publication – February 2015*
   4. *Access Link - IEEE Games Media Entertainment*

ii. The paper studies zone changes, distribution of team members, positional information using time series clustering via a fuzzy approach. It investigates how behavior varies across these measures as a function of the skill level of teams, from novice to professional players (4 tiers).

iii. The presence of towers and creeps disturb the balance of the movement.

iv. In addition to the space-time data of players, the DotA2 map needed to be constrained based on the underlying terrain. This limits the combinations of places players can be as a sample of total possible outcomes.

v. One of the underlying features is that players with more expertise change zones on the accessible terrain-compliant map more often, and studying how this contributed to victories is included in the study.

vi. A one-way ANOVA test was used to test the difference in average team distance across entire matches. And distribution of team on the map was analyzed using Euclidean distances. Professionals have a small average distance and small variance. The novice tiers have the highest average and largest variance.

vii. Time series clustering was used to find the patterns in movement over time. The behavior is assessed from two perspectives – finding players with similar records, and scrutinizing why this movement was created. The permutation distribution makes the complexity of the time-series, where similarity is determined by the divergence between two player's time series. This metric is constant across space and time and is computationally efficient (linear time).

viii. Combining the prior method with fuzzy clustering to create three general clusters for three lengths of games (short, average, long). Professional players have shorter games.

ix. The results show that where there is more interaction between the team and there is tight-knit fencing and perform well-strategized coordinated movement, the victory is more apparent.

2. MY IDEA AND HOW WOULD WE GO ABOUT IT (IF WE DID)

The idea is for a DotA2 personalized training module that –

→ Assesses the past behavior of the player within the context of –

1) A function carried out
2) A hero with support items
3) The utilization of a hero for successful functioning in a role

→ The decisions taken in a specific circumstance with respect to the first point and the need of the circumstance from a team point of view (for wins) and from a personal improvement point of view.

→ Earning gold, last hits, tower defense/offence, one-on-one combat and team combat is part of this feedback. All this is given by pinpointing the circumstance in a replay where decisions could be taken differently and would have probably earned better results. This is easier to perform for an individual. For a team, each player is given a relative feedback.

→ The analysis performed using mathematics and statistics is deciphered in terms of game physics and player actions and converted to a causal inference graph that then can be easily converted to natural language explanation for a user.

How has the prior research fine-tuned this idea…

In the first study we saw the distribution of players in the three skill categories and the peculiar observation where it wasn't the very-high skill players that were of the lowest number, but the high skill players that were so. That is peculiar because very-high skill players would understandably require better ability than the previous group and would be rarer. The reason behind this distribution may be that the conversion the learning curve is very slow to begin with (maybe even stops before it has a chance), and then picks up after a certain threshold is crossed. Hence, this feature would be very useful for the normal skill players.

Another observation that may be made is that some algorithms seemed to have been used in all the studies repeatedly, but their primary aim was at predicting game outcomes not improving player skills. In this context, any algorithm that needs to be used would have to be mapped to actual game scenario and decision descriptions from an intermediate algorithm result. For example, a learning algorithm based on a specific set of features must be convertible to a cause-effect network such as one below –

a. *Performing these movements in this order in this circumstance worked the maximum times EXCEPT in cases where this scenario happened.*
b. *In the other sequence of moves performed, it resulted in the opposition taking advantage of this /destroying this/winning because of this scenario.*
c. *Getting better at using this item will help you perform this function well, since that is where you seem to have most difficulty.*

1) And to be able to create this, it is important to use explainable AI, primarily using associations, guided random forest decision trees, constrained combination search and anomaly analysis. These mentioned methods may be converted to actual game-related clauses and then be consequently put into natural language along with the relevant snippets of replay.
2) Another focus that was demonstrated by the study is the importance to give to inter-player interactions (combat and collaboration both). This is something that a psychologist will be very involved in and will assess the approaches different players take in fight/flight/freeze mode. Modeling this correctly will make second-order and team fight analysis more informed. Team fights will need special considerations since defining a team fight, deciding the end of a team fight, and identifying offence, support, and collateral damage and changes during will affect the feedback for the team and individual players both.
3) Another observation was that Captains Draft didn't make a difference in the outcome which means that overall strategy and picking of heroes for functions is a major part of feedback too.
4) In the combinatorics of the different aspects, some of the contradictions and statistical impossibilities ought to be weeded out.
5) On the whole, the experience must be interactive, modeling the feedback based on what the players' and teams' intents were, and not what the training system's assumptions were.

How do we go about it…

The entire process may be compartmentalized into the following phases –

1. *Discussion of novice, intermediate, and expert player strategies with a panel of players, Valve psychologists, and algorithm developers.*
2. *Categorization of the above information into team play and individual play. Individual play will cover player history of choices and playing style, last hits, current game scenario analysis and decision analysis, and random peer review processing. Team play will cover strategic weaknesses in specific circumstances in the current game, alternative replays for different team decisions taken, hero selection guidance and function fulfillment guidance, critical period pinpointing and detailed cause-effect description.*
3. *Point 2 is carried out in an iterative manner – first with the players and psychologists, then with algorithm designers and AI software developers, and then testing is carried out with the player sand outcomes as judges for the efficiency of a slice of the implementation, then iterating over improvements and errors.*
4. *Results of the released product would be marked by the conversion of players of normal to high skill levels. And the coverage of expert creative moves performed by professional players.*