We believe this is an interesting result in itself, but it also has a real world utility. The anonymity of online gaming and the ease of obtaining new accounts often leads to unwanted behavior by a minority of players. This can manifest in a number of ways: abusive communication, cheating and matchmaking manipulation. Unchecked abusive communication often manifests itself in terms of sexist and homophobic abuse, which leads to an unpleasant and hostile game environment. Matchmaking manipulation occurs when a player uses a different account (usually purchased illegally) with a different skill rating than the player has themselves. This leads to unbalanced games.

This presents a challenge for the developer of these games: simply banning accounts often does not work. As Dota 2 is a free to play multiplayer game, identifying players is especially challenging. A single player can create multiple accounts anonymously merely by providing different email addresses. As a result, unwanted displayed by some players towards one another [16] and the rise of illegitimate secondary markets to sell accounts with higher ranks present a serious problem. Players who are banned from the game for bad behavior may continue to play using a fresh account. Additionally, without the ability to verify and link a person to an account, it is easy for players to cheat in amateur online tournaments by playing in the place of another player. A lot of manual effort and luck is required to determine if someone cheated this way. In a recent example, a player was caught cheating in the $30,000 CSL Dota 2 tournament for college students. The cheater was only caught after officials were tipped off [19] due to obviously strange behavior. By using machine learning techniques to identify the players based on their behavior, cases like this would be easily identifiable and solvable.

Learning player identity by their behavior in order to take action against them is also more effective compared to taking action based on account names, IP addresses or hardware ID bans. Players can just buy or create new accounts if their original one is banned; IP addresses are rarely static [24] due to NAT gateways and banning a range of address may lead to banning innocent players; Hardware ID bans may be effective in the short term, but hardware can still change hands between people. A system which can recognize player behavior can be more effective in the longer term, especially as we explore from a low-level and fine-grained view of the data rather than high-level behavioral elements.

ABSTRACT
Dota 2 is a popular, multiplayer online video game. Like many online games, players are mostly anonymous, being tied only to online accounts which can be readily obtained, sold and shared between multiple people. This makes it difficult to track or ban players who exhibit unwanted behavior online. In this paper, we present a machine learning approach to identify players based on a ‘digital fingerprint’ of how they play the game, rather than by account. We use data on mouse movements, ingame statistics and game strategy extracted from match replays and show that for best results, all of these are necessary. We are able to obtain an accuracy of prediction of 95% for the problem of predicting if two different matches were played by the same player.

INTRODUCTION
Dota 2 is a popular, multiplayer online video game. Like many online games, players are mostly anonymous, being tied only to online accounts which can be readily obtained, sold and shared between multiple people. This paper presents an automatic way of identifying a player by establishing a ‘digital fingerprint’ based on how a player plays the game rather than relying on account information. It shows that incorporating game-centric information into the model is necessary for the best performance, when compared to existing context free digital forensic techniques which rely on mouse movements.

Using a combination of game information and mouse movement analysis, we are able to identify if two different matches were played by the same player with an accuracy of 95%.

We believe this is an interesting result in itself, but it also has a real world utility. The anonymity of online gaming and the ease of obtaining new accounts often leads to unwanted behavior by a minority of players. This can manifest in a number of ways: abusive communication, cheating and matchmaking manipulation. Unchecked abusive communication often manifests itself in terms of sexist and homophobic abuse, which leads to an unpleasant and hostile game environment. Matchmaking manipulation occurs when a player uses a different account (usually purchased illegally) with a different skill rating than the player has themselves. This leads to unbalanced games.

This presents a challenge for the developer of these games: simply banning accounts often does not work. As Dota 2 is a free to play multiplayer game, identifying players is especially challenging. A single player can create multiple accounts anonymously merely by providing different email addresses. As a result, unwanted displayed by some players towards one another [16] and the rise of illegitimate secondary markets to sell accounts with higher ranks present a serious problem. Players who are banned from the game for bad behavior may continue to play using a fresh account. Additionally, without the ability to verify and link a person to an account, it is easy for players to cheat in amateur online tournaments by playing in the place of another player. A lot of manual effort and luck is required to determine if someone cheated this way. In a recent example, a player was caught cheating in the $30,000 CSL Dota 2 tournament for college students. The cheater was only caught after officials were tipped off [19] due to obviously strange behavior. By using machine learning techniques to identify the players based on their behavior, cases like this would be easily identifiable and solvable.

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BACKGROUND
Dota 2
Defence of the Ancients (Dota) 2 [2] is a popular free-to-play multiplayer online battle arena (MOBA) video game developed by Valve Corporation. In Dota 2, the player controls a single hero as part of a team of five players competing against an opponent team. Each hero has their own unique abilities and characteristics, for example some heroes focus on dealing damage with spells and abilities, while other heroes use passive abilities to augment their attacks. To win, the team must destroy the opponent’s base structure, known as the Ancient, located deep in the opponent controlled side of the map. The map is split into three lanes, with towers that must be destroyed in succession. Weaker, uncontrollable units...
ways. Firstly, the gameplay for Starcraft 2 and Dota 2 are

Additionally, heroes gain gold throughout a match which can be used to purchase items. Items provide powerful bonuses and abilities to a hero. Every hero has 6 slots in their inventory in which they can place purchased items. Items can also be placed in the stash or backpack, but do not provide any bonuses when placed there. Gold is gained from multiple sources, most notably by getting the killing blow on creeps, killing opponent heroes, destroying opponent buildings and passively over time.

The map in Dota 2 is asymmetrical and split in half for the two teams: Radiant and Dire. Figure 1 shows a representation of what the map looks like. Playing on different sides leads to slightly different strategies due to the asymmetry. The explanation of other more complicated mechanics in the game, such as the neutral jungle creeps and runes are omitted as they do not form any part of the features or data extracted in this work.

Related work

Starcraft 2 player identification

The problem of player identification based on play style and behavior has been explored before in the game of Starcraft 2. Liu et al. [17] first looked at using machine learning algorithms to identify a Starcraft 2 player from features extracted from match replays and followed up with further research [18] on predicting a player’s next actions based on their previous actions in the match.

Their work has a similar goal to ours to predict players based on behavioral data. However, our work differs in multiple ways. Firstly, the gameplay for Starcraft 2 and Dota 2 are different as the player controls a large number of units in the former and only one in the latter. This means the features used for player prediction in Starcraft focused more heavily on the strategy and build order of players rather than fine grained data such as mouse movement. Secondly, Liu et al. focussed on the classification from a fixed pool of players. While we also do the same, we go further and look at classifying pairs of matches belonging to the same player. This allows our predictions to be much more general and not need to be retrained on every new pool of players in the dataset.

Dota 2

There has been a variety of previous work in data analysis on Dota 2. Much of the growing research in Dota 2 comes from the wealth of data provided from the replay system, which ranges from the positions of each player’s mouse cursor to the health points of each creep entity.

One area of exploration with Dota 2 data is the classification of player roles. As Dota 2 is a team game, each player on the team typically fulfils a certain role in a match, similar to traditional sports. Gao et al. [13] presented positive results in the identification of both the hero and role that a player played using a mix of performance data and behavioral data that involved ability and item usage. Eggert et al. [10] took a further step in feature generation for role classification by constructing complex attributes using low-level data from a parsed replay of a match. This included features such as player positional movement and damage done during teamfights.

Data analysis in Dota 2 does not only involve analysis of in-game data using replays. Hodge et al. [14] used a mix of pre-match draft data such as the history of a player’s performance on different heroes and in-game data of game states at different sliding window intervals to predict the outcome of unseen matches. Taking match outcome prediction further, Yang et al. [26] were able to predict match outcomes in real-time as the match progressed, to get the probabilities of each team winning at every minute of a match. For real-time data, they showed data from later stages of a match were much more informative, as early portions of a match were often similar to other matches. Their work was compared with work from Conley and Perry [7], whose focus was in creating an engine for hero pick recommendations based on win predictions, and with work from Kinkade and Lim [15], who also investigated combinations of in-game statistics and draft picks outcome prediction. Drachen et al. [9] studied how team behavior varied as a function of player skill, specifically on the movement and positioning of heroes by players as spatial-temporal data. This contrasts with most other studies, which have focused on only temporal data like the gold and XP per minute statistics.

There is also existing research that uses qualitative data rather than quantitative data. Nuangjumnong and Mitomo [20] conducted a survey on players which showed correlation between the leadership style of players and the role they played in the team. Summerville et al. [23] studied the drafting phase of the game to find common trends and predict the draft sequence. In particular, because the draft sequence was described as a list of words, they chose to use a one-hot encoding with a categorical cross-entropy loss to encode the hero names.

Other video games

Player behaviour in video games has often been modelled to gather meaningful data for further analysis. Pfau et al. [21] applied machine learning techniques to construct deep
player behaviour models in the video game Lineage II. These models can be applied in online crime detection for cheating and for autonomous testing of the game. Bakkes et al. [5] provided approaches to player behavioural modelling with the goals of improving game AI and improving game development. Drachen et al. [8] developed in-depth behavioural models for players in the video game Destiny to identify distinct play-styles and profiles players can be clustered into.

Mouse dynamics
In research unrelated to Dota 2, many studies have investigated the area of using mouse dynamics to detect user identity. This is a behavioral biometric technology that analyses different mouse movement attributes, such as the velocity or curvature of the mouse cursor. A significant portion of Dota 2’s gameplay revolves around the use of mouse clicks and movements, combined with occasional key presses. Bhatnagar et al. [6] compared the use of mouse and keyboard dynamics as a biometric technique and stated that keystroke dynamics have lower predictive accuracy, but mouse dynamics data tends to be inconsistent and error prone due to the varied hardware input devices.

Mouse movement data extraction can be done explicitly by using a predefined activity, or implicitly by monitoring typical activity without a specified task [11]. For example, Gambao and Fred [12] used a simple memory game to extract their data. This method allows for well-defined actions. Feher et al. [11] went further by categorising mouse movement features into distinct hierarchies, which allowed for precise categorisation of various different types of mouse movement. Their results were compared with a histogram based method from Awad and Traore [4] of aggregating different types of mouse action and obtained noteworthy improvement in the accuracy of their models.

METHODOLOGY
In this paper, we investigated the use of three different feature-sets to determine who the player is. Each feature-set explores a different aspect of the game, to see which aspects have a greater effect in predicting players. The mouse movement features are fine-grained biometric features that directly capture player behavior based on how they move their mouse. The game statistics features are higher level results of player behavior. For example, an aggressive player may tend towards higher kill/death statistics compared to a more passive player. Finally, the itemization features capture both strategy and gameplay behavior of players. Players typically have strategies (or builds) that they use on the same hero which is reflected in the items they buy. The position of the items in the inventory also indicate specific player behavior based on their personal keyboard bindings for the game.

The features are used both individually and in combination with the other features on three different machine learning models (logistic regression, random forest classifier and multi-layer perceptron) to find the best model and feature combination for predicting player behavior.

Data collection and processing
A combination of the OpenDota [3] API and Valve’s official API was used to download replays. In particular, the OpenDota API allowed many aspects of the replays to be controlled, such as the game mode and hero id, leading to less random variables. The following list of parameters were used for our datasets:

- **Game mode**: All pick
- **Team**: Radiant
- **Date**: Before 18 November 2018 (to avoid changes from patch 7.20 affecting some of the existing work)
- **Hero id**: Constant as the same hero was used for all the datasets

Match replays were parsed using clarity, an open source parser developed by Martin Schrodt [22]. It allowed fine grained data to be extracted from each replay on each game tick. After the data was extracted, more processing was done to encode the data into useful features to create our dataset.

Mouse movement features
The mouse movement features extracted from the Dota 2 match replays followed the concept by Feher et al [11] on forming a hierarchy of atomic actions such as left click or mouse move and complex actions made up of multiple atomic actions, such as mouse drag. As the data available from replays are less granular and do not contain specific data such as mouse click down and mouse click up, the addition of keyboard presses were combined to form the complex mouse actions in this work. Two classes of mouse actions are defined: atomic and complex.

**Atomic mouse actions**
The four atomic mouse actions are as follows:
1. Mouse movement sequence
2. Attack command
3. Move command
4. Spell cast command

A mouse movement sequence is defined as a sequence of positions. Rather than using a fixed interval of time, a threshold $\tau$ is defined to end the sequence if no change in cursor position has occurred within the threshold time. This more naturally records a sequence of mouse movements to not break up a sequence in order to fit within a fixed time interval. A larger threshold increases the average number of actions in the sequence. A threshold of 500 milliseconds was used in Feher et al.’s [11] study. This was reduced to 300 milliseconds for capturing Dota 2 mouse features as it was found a 500 millisecond threshold created fewer and longer mouse movement sequences than expected.

Each movement sequence consisted of three vectors of length $n$, where $n$ is the number of game ticks:
- $t = \{t_i\}_{i=1}^n$ - The game tick
- $x = \{x_i\}_{i=1}^n$ - The x coordinate sampled on game tick $t_i$
- $y = \{y_i\}_{i=1}^n$ - The y coordinate sampled on game tick $t_i$
Finally, because the feature vectors for a mouse movement sequence are of varying length, some statistical values must be taken. The minimum, maximum, mean and standard deviation are used leading to a total of 38 features for complex mouse action.

**Game statistic features**

In-game statistics are a useful way to determine player performance in Dota 2. Many community websites [1, 3] track these statistics to let players view the performances of their match history. Many existing studies [14, 15, 25, 26] also use these features, especially for predicting performance of teams and players.

The statistics extracted for this work are:

- Kills
- Move commands on position per minute
- Assists
- Attack commands on target per minute
- Deaths
- Attack commands on position per minute
- Gold per minute
- Spell cast commands on target per minute
- CS (creep score) per minute
- Spell cast commands on position per minute
- XP per minute
- Spell cast commands with no target per minute
- Deaths
- Actions per minute
- Move commands on target per minute
- Assists
- Hold position commands per minute

Most of the statistics are taken as per minute average rather than total, because they can vary greatly depending on the length of the game. In general, the game statistics are strong indicators of performance as winning teams usually have higher gold and XP numbers. They can also provide behavioral information, for example aggressive players may often get more kills than more passive players, they may get more deaths as a result as well. Further, there are a few different methods for players to accomplish the same action, which can be revealed based on whether they use commands on targets or on positions.

**Itemization features**

The items a player buys on their hero had been shown by Eggert et al. and Gao et al. as a strong indicator of the hero selection and role of the player. By itself, itemization is likely not enough to tell the difference between players, as multiple players on the same hero are very likely to buy the same items. However, items can be placed into different inventory positions, which becomes a more personal choice by players. Moreover, many items in Dota 2 have active abilities. The inventory positions of the item therefore can reflect a player’s keyboard bindings. It is not possible to extract a player’s personal settings from a replay, so using item positions are a

| Feature                      | Definition                                                                 |
|------------------------------|-----------------------------------------------------------------------------|
| Angle of movement            | $\theta_i = \arctan\left(\frac{\delta y_1}{\delta x_1}\right) + \sum_{j=1}^{n} \delta \theta_j$ |
| Curvature                    | $c = \frac{\delta \theta}{\delta s}$                                      |
| Rate of change of curvature  | $\Delta c = \frac{\delta c}{\delta s}$                                    |
| Horizontal velocity          | $V_x = \frac{\delta x}{\delta t}$                                         |
| Vertical velocity            | $V_y = \frac{\delta y}{\delta t}$                                         |
| Velocity                     | $V = \sqrt{\delta V_x^2 + \delta V_y^2}$                                  |
| Acceleration                 | $V' = \frac{\delta V}{\delta t}$                                          |
| Jerk                         | $V'' = \frac{\delta V'}{\delta t}$                                         |
| Angular velocity            | $w = \frac{\delta \theta_i}{\delta t}$                                   |

Table 1: Basic mouse movement features.

$n$ can vary between different movement sequences for longer or shorter sequences. These vectors are further processed to give the list of mouse movement features shown in table 1, based on Gamboa and Fred’s [12] features.

The other three atomic actions consist simply of the game tick, x, and y coordinate. They represent in-game intent of the mouse movement. For example if a player right-clicks on the terrain, it is a move action to move their character, but if a player right-clicks an enemy entity, it is an attack action.

**Complex mouse actions**

The combination of a mouse movement sequence and one of the three command actions creates a complex mouse action. There are three complex mouse actions, each corresponding to their respective atomic command. Complex mouse actions represent a mouse movement sequence leading up to a command. Each of the three complex actions are recorded in the same way, but record different kinds of data. For example, the complex move action will be recorded throughout a match, while the complex spell cast action will typically occur only during teamfights.

In addition to the features mentioned in table 1, two more features are included for complex mouse actions:

- $t_n$ - The number of game ticks between the last mouse position of the movement sequence and mouse position of the command.
- $d$ - The distance travelled between the last mouse positions of the movement sequence and mouse position of the command.
we could successfully identify one player out of the pool of while others only had 1 or 2 matches. The goal was to see if when looking at only starting items. This reduces the large which restricts the number of items from about 300 to 30

The second experiment took a more generic approach. Rather than predict out of a static pool of players, the goal was to identify if two matches belonged to the same player or not. The inventories are sampled once at the beginning of a match and once at the end to prevent variance. Items sampled at the beginning will not be affected by variables such as performance as the game has just started. Items sampled at the end are similar, as most items that players want will have already been purchased and are less affected by the flow of the match. The items and their positions are then encoded with multiple methods: feature hashing, one-hot encoding, selective one-hot encoding and item difference.

Selective one-hot encoding only used a small subset of items deemed more useful for player prediction. Two subsets were chosen, starting items and boots. There are only a small number of items a player can buy at the start of a match, which restricts the number of items from about 300 to 30 when looking at only starting items. This reduces the large number of features that one-hot encoding generates (∼ 300 items × 6 inventory locations) to a reasonable number. Boots are a special case of items as almost all heroes will buy some form of boots. There are 6 types of boots in the game, most of which have an active ability. Because different boots have different abilities, but all give an important movement speed increase the player characters, different players are likely to choose different types of boots based on their personal playstyle. Furthermore, the active ability makes the position of the boots in the inventory an important attribute we can take advantage of. This allowed for precise identification of both the type of boots and the inventory positions they occupy as data.

EXPERIMENTS
Two different experiments were done to explore the problem of predicting player identity in Dota 2 based on the features discussed earlier. A dataset comprising of 93 players with 356 matches was created. There was a mix of number of matches per player, with some players having 10 matches in the dataset while others only had 1 or 2 matches. The goal was to see if we could successfully identify one player out of the pool of players in the dataset given a single match.

The second experiment took a more generic approach. Rather than predict out of a static pool of players, the goal was to identify if two matches belonged to the same player or not. In this approach, there is no concept of individual players, only the binary choice of whether the two given matches were played by the same person. A combination of pairs of matches were created from the original dataset, which gave 3071 combinations where two matches belonged to the same player. The number of combinations where two matches belonged to different players was much larger, but was randomly filtered down to 3071 to ensure no bias towards the negative samples.

The features used in the second experiment differed slightly from the first experiment because all matches have different lengths, making it difficult to compare the features from two matches without further modification. Further statistics are calculated for each mouse movement feature over the entire match. For example, the horizontal velocity of a mouse action creates four features: the mean, standard deviation, minimum and maximum horizontal velocity of each individual mouse action. There are many drawbacks to this approach, most notably the loss of data from taking an average of averages, as the thousands of mouse actions are reduced to only a small number of statistics. To alleviate this issue, matches are split up into portions for each portion to have its own statistics. This also allows each individual portion to be analysed. However, this method is not scalable, as more portions means more features, leading to the curse of dimensionality.

Experimental design
The mouse movement, game statistic and itemization features were explored both separately and together to identify their performance in player prediction. It was assumed that in the dataset, all replays that were downloaded from the same account were matches by the same player.

As the different features had different dimensions, each were evaluated with separate models, with the results of each model combined using a simple multi-layer perceptron with 1 hidden layer. Figure 3 shows how matches split up into each feature and model separately before being combined. A multi-layer perceptron is used as the combination step so it can learn the relative weights for each feature, rather than use them all equally in a voting scheme or set arbitrary weights to them. Further, this approach is modular and allows features to be added or removed easily to test the performance of different combinations of features.
RESULTS

Player identification (experiment 1)

Mouse movement features
First, the mouse movement features were evaluated individually to give an indication as to which type of complex mouse action is more informative for player prediction. Figure 4 shows that mouse movements following an attack action were the most predictive, with movements following a spell cast being the least predictive. It is important to note the distribution of complex mouse actions are not equal, with an average of 20%, 78% and 2% for attack, move and cast actions respectively. This directly affects the number of data points available for training and testing.

Taking this into account, complex attack actions make a strong case for being the most effective at predicting player behavior, as they are less common, but more predictive than complex move actions. Complex move actions seem to be too common to be a strong indicator for player behavior. They are sent in the order of a few thousand commands in every match, due to how movement and positioning are fundamental parts of Dota 2's gameplay. This commonality can lead to difficulty in distinguishing between different players, especially when players are sending move commands multiple times a second, making the mouse movement sequence very short. Complex spell actions should follow the pattern for complex attack actions, since they are also rare and unique compared to move actions. However, it seems their rarity (2%) affects their usefulness.

When looking at the mouse actions used together in figure 5, we can see the differences between each machine learning model clearly. The random forest classifier has perfect precision but low recall, indicating a lack of false positives predicted. From the test set, we found 0 false positives and a large proportion of false negative predictions. There are still true positive predictions, so the model is not predicting only negatives, but is highly biased towards it. This suggests a specific player’s (the positive sample) behavior is difficult to differentiate from another player in most cases, but when it is detected it is very obviously from the specific player.

The performance of logistic regression was quite noteworthy as it matches the neural network in all three performance metrics. This is an improvement compared to using individual complex mouse actions. This also shows that the combining network was able to learn useful weights to apply to each of the three logistic regression models and such a mixture of different complex mouse action types are more useful than each mouse action alone.

Game statistic features
Using game statistic features gave a set of different results compared to using mouse action features, with the neural network performing poorly and the other two models achieving very high accuracies. As shown in figure 6, the random forest classifier had perfect results. To confirm this, we ran further cross validation with varying values of \( k \) up to 12 for additional trials. It was found that the accuracy only fell twice, at \( k = 2 \) to 0.95 and at \( k = 8 \) to 0.98. This gives the strong performance merit, suggesting there exists a combination of rules in a decision tree for player in-game statistics that easily identify players uniquely.

Itemization features
Each encoding method of itemization gave different performances, with the random forest classifier and multi-layer perceptron giving the same pattern for each encoding method, as shown in figure 7. Firstly, encoding with boots only data had
the lowest accuracy of all the encoding methods. This makes sense as it uses strictly less items compared to other encoding methods. This represented a trade-off for computation of features and accuracy. For comparison, the one-hot encoding of only starting items gets 4%, 6% and 7% more accuracy for each model respectively, but uses 186 features compared to the 42 features of encoding only boots data.

We also found a small improvement from using starting items only compared to using all items with one-hot encoding. Recall that the encoding of all items is sampled twice in a match, once at the beginning and once at the end. The close performance of the two encoding methods suggests a few things. Firstly, the massive increase in binary features does not heavily impact performance. The encoding of all items contains about 9 times the number of features (281 items vs 31 items) but the accuracy deviates by less than 5%. Secondly, though the starting items do not have the second sample of items at the end of the match, it still predicts better in two of the three machine learning models. This shows the items locations of at the start of a match is more useful in player prediction than at the end of a match. This makes sense from the game’s perspective, as items a player buys throughout a match is often dependent on the strategy, composition and context of their team, the opposing team and how well they are doing, so there is more variance in end of match items compared to the start of matches. Further, many matches end before a player finishes buying all items they need, so item locations recorded at the end of a match could be temporary and different from other matches by the same player, depending on the context of the match.

Combined features
Combining the features together gave mixed results in most cases. There were some improvements in specific cases, but there were also cases where performance decreased.

Logistic regression was able to predict well in general, with the combination of game statistics and boots achieving 99% accuracy. There was also an interesting anomaly in combining mouse movement, game statistics and one-hot encoding of all items that had a drastic reduction in accuracy. This may be due to the combination of one-hot encoding of items and mouse movement being a bad combination, as it was the only other combination that had lower than 90% accuracy.

The random forest classifier showed reduced accuracy in most combinations using mouse movements compared to using the features alone. For example, the various itemization encoding methods had about 85-90% accuracy and game statistics had close to 100%. However, when any of these features are combined with the mouse movement data, the accuracy drops. It can also be seen in table 2 that the combination of itemization and game statistics do well, so it is only the mouse movement features that is an issue for this model. Recall that the precision for using mouse movement features in the random forest classifier was extremely high with low recall, which reduced its accuracy. The lack of accuracy even when combined with accurate features such as game statistics shows that it is not enough to combine all features together, and bad features add a lot of noise to the random forest model.

Finally, the multi-layer perceptron was able to combine features together better. Though it performed poorly using only statistics, the addition of mouse movements and itemization features were able to help boost its accuracy. Interestingly, the better individually performing item encoding methods were not always better than others when combined with other features. For example, using mouse features with the hashed items and mouse features with boots only gave similar accuracy, even thought the hashed encoding was more accurate alone compared to the boots only feature.

Same player identification (experiment 2)
Mouse movement features
Figure 8 shows the performance of the three machine learning methods. In general, logistic regression performs much worse for this problem, regardless of how the match is split into time-slices. This shows the non-linear nature of this problem compared to the first one. Splitting the match into multiple time-slices doesn’t help or hinder the accuracy for logistic regression, which shows it is unlikely an issue of too many features affecting the performance, otherwise a greater fall in accuracy would be expected from figure 9.
Table 2: Accuracy of each model on each feature combination. The accuracies highlighted in red are of particular interest for discussion.

The overall accuracies of all three models were also lower compared to the first problem, which shows the difficulty of this problem in comparison, when there is not a small and limited pool of players.

Moreover, using additional time-slices caused less accurate predictions, which suggests the existence of noise when the featureset is repeated for each time-slice. Both the random forest classifier and multi-layer perceptron lost accuracy as a match was sliced into more parts and used together. This shows that although slicing gives more fine-grained data, the additional noise is detrimental to player prediction. We also found that each individual time-slice has little effect on the accuracy of predictions, as figure 10 show little performance difference between each individual time slice. This is rather unexpected, since the strategy and gameplay in different phases of a Dota 2 game change, so one would expect the mouse movement behavior of players to change as well.

Game statistic features

Figure 13 shows the correlation matrix between pairs of matches by the same player. We can see how each statistic feature of one match is correlated to the statistic feature of another match from the same player. For instance, the CS, denies, gold per minute, XP per minute and CS per minute statistics are well correlated with each other, even across different matches. It would be expected for these numbers to be correlated in the same match, as creeps directly affect the gold and XP gained by heroes. However, seeing the statistics continue this trend across different matches suggest they are also tied to specific player behavior.

It should be noted that the correlation matrix is mirrored across the diagonal. This is a result of the combination step, where matches are combined into pairs of \{match0, match1\} and \{match1, match0\} and should not be taken as a meaningful result. Due to the way the clarity parser runs through matches chronologically, a bug in the library prevented us from split-
One-hot encoding of all items performed similarly to the starting item feature for game statistics. However, when using the game statistic features, showing a strong correlation between game statistics and player prediction using decision tree based models. This seems to be due to decisions being able to determine ranges for statistics for player prediction. For example if one statistic is always in a similar range across multiple games, it is likely to be the same player.

**Itemization features**

Figure 11 shows the accuracy with different itemization encodings and features. For these features, using only boots was the best indicator for random forest and multi-layer perceptron, while the item differences were best for the logistic regression model. Once again, logistic regression did not have good results compared to the other models. The only exception is the item difference method of encoding. This is a bit of an anomaly, as the trend suggests logistic regression is not suitable for this classification task.

The difference between the item difference encoding and all other features is that features are not duplicated for the pair of matches. For all other features, the features for both matches are used together, to see if features across the two matches may be correlated. The game statistic features shown earlier display this kind of correlation. However for the item difference, the presence or absence of the same item on an inventory slot is encoded and so there is no duplication of features. This contrast reduces the complexity of the feature, which allowed the logistic regression model to perform comparably to the other two models where all other features could not.

The one-hot encoding of all items performed similarly to the one-hot encoding of only starting items. This was surprising because the one-hot encoding of all items contained 250 more items, which translates to 1500 more binary features. As was the case in the last experiment, the increased number of binary features had little effect on the performance of the models. The gap between the two methods is smaller than previously, which means just using starting items to differentiate between two players is more difficult than identifying a single player.

This suggests a more diverse pool of players leads to more similarity in starting items between any two players.

**Combined features**

Strong results were found for combining features together, unlike the first experiment. All three models were able to find improvements from using the different features together. For instance, the logistic regression model could not accurately predict if two matches belonged to the same player for all features except for the item difference feature. However, when combining the item difference feature with the poor performing mouse movement and game statistic features, we were able to get up to 10% higher accuracy on certain combinations. For the multi-layer perceptron, we found precision generally increased with more feature sets at the cost of recall. This led to a smaller increase in accuracy of 5-7%. The high precision is more beneficial compared to high recall because less false positives means predictions for two matches belonging to the same player are more unlikely to be wrong, even if we may miss some predictions due to false negatives.

We found the random forest classifier was able to achieve the highest accuracies in this problem when multiple features are combined together. Figure 12 shows the improvement we found. The model was able to go from 81% correct predictions using only starting items to 91%-95% correct predictions from a combinations of starting items and other features. The highest 95% accuracy came from a combination of starting items, game statistics and mouse movement features.

**FUTURE WORK**

*Fine grained information on mouse movement features*

Although we have been successful in using mouse movement features to predict players with good results, there are still many details that are unknown. For example, although we take a number of attributes for each mouse movement sequence recorded, the context such as target entity or current hero properties are not recorded. Including the context for each mouse movement would allow us to learn if certain actions under certain circumstances are more indicative of player behavior.
Multiple heroes from the same player

In this paper, we focused our research on the exploration and combinations of features and models for player prediction so we kept the hero used constant throughout the experiments. The same methodology is likely to work on different heroes, but it is not known how it would work in a dataset that contained multiple heroes. This is because the difference in play-style of different heroes would interfere with the difference in player behavior, so it would be interesting to see how this work could be extended to a multi-class classification of this case.

Deep Learning

Our work primarily used traditional machine learning models such as logistic regression and random forest classifiers. With the increasing popularity and performance of deep neural networks, it would be interesting to compare how a accurate a deep learning model could predict players compared to these traditional machine learning models.

Automated detection tool

Finally, because we have found strong results for classifying with random forest classifiers, our models can be applied to create a real world tool for automatic detection. The tool can be prototyped to accept replays and return predictions. Successful prototyping with a high accuracy and high precision can lead to the tool being used in online tournaments as a method to prevent cheating. The creation of such a tool will also help to refine the model by exposing it to a much larger variety of players and matches.

CONCLUSION

This work explores the extraction and use of various features from Dota 2 match replays, in combination with mouse tracking techniques, to predict who the player is based on their in-game behavior. We explore two approaches to this problem. Firstly, we predict identity from specific player from a pool of players. For this approach, we find that the use of game statistics with a random forest classifier can achieve high prediction rates but it could not combine poor features with good features without losing a lot of accuracy.

Our second, more universal approach centres around matching (or otherwise) players from two different matches from the set of all players. This approach is more generalizable to the large player-base. We find the combination of game starting items, mouse movements and game statistics using a random forest classifier can produce an accuracy of 95%.

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