Data gathering and analysis in gaming using Tobii Eye Tracking

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E-sports is growing and the price pools in e-sports tournaments are increasing. Valve’s video game DotA 2 is one of the bigger e-sports. As professional gamers train to increase their skill, new tools to help the training might become very important. Eye tracking can give an extra training dimension for the gamer. The aim of this master thesis is to develop a Visual Attention Index for DotA 2, that is, a number that reflects the player’s visual attention during a game. Interviews with gamers combined with data collection from gamers with eye trackers and statistical methods were used to find relevant metrics to use in the work. The results show that linear regression did not work very well on the data set, however, since there were a low number of test persons, further data collection and testing needs to be done before any statistically significant conclusions can be drawn. Support Vector Machines (SVM) was also used and turned out to be an effective way of separating better players from less good players. A new SVM method, based on linear programming, was also tested and found to be efficient and easy to apply on the given data set.
This master thesis in optimization and systems theory was written by Jonas Avemo, a master student at the Royal Institute of Technology in Stockholm, in collaboration with Tobii Technology. The University supervisor was Professor Krister Svanberg and the supervisor at Tobii Technology was Tobias Lindgren. The thesis was written at the Tobii’s office in Stockholm.
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INTRODUCTION

E-sports is growing and during 2013 it was estimated that more hours were spent on watching e-sports than watching television in Sweden (Rosholm, 2014). The biggest DotA 2 tournament of 2014, The international, has a prize pool of over ten million dollars (Valve, 2014) and the prices of e-sports tournaments are growing (e-Sports Earnings, 2014). With professional gamers earning a lot of money from tournaments, practice is an important factor in becoming a better gamer. In this context, new tools for training can be used by professional gamers to train and get an extra advantage.

This project’s goal is to use a Tobii proprietary software and hardware unit to gather statistically significant amounts of data from players of all skill levels in a video game title (Valve’s DotA 2) and then to develop domain specific formulas to apply to this dataset. The aim of the model is to quantify the players visual attention, that is, how aware was the player of the surroundings during a game. These formulas will be part of software that will act as a training tool, to help gamers improve their performance.

1.1 EYE TRACKING

An eye tracker is a device that can measure the position, direction and movements of eyes. The eye tracker uses near-infrared lighters and optical sensors. The lighters irradiate the eyes with near-infrared light which create reflection patterns on the eyes. The optical sensor then gets an image of the user and the user’s eyes. Image processing is then used to find the eyes position and direction, which then can be used to calculate where the user is looking, the gaze point. This process is visualized in Figure 1 (Tobii, 2015).

1.2 DotA 2

DotA 2 is a MOBA (Multiplayer Online Battle Arena) game developed by Valve. Two teams with five persons in each team face each other. Every player controls one hero and every hero has several abilities that they can use as well as hitting or shooting. The abilities become stronger as the hero’s gains levels, which they do throughout the
game. Every hero also has room for six items that can make the hero stronger in different ways, items are purchased with gold which you earn through the game. The goal of the game is to destroy the enemy ancient, a building located in the enemy base which is protected by towers. To help destroy the towers and finally the ancient, are creeps, computer controlled characters that spawn every thirty seconds and run in lines toward the enemy ancient and the creeps attack every enemy unit in their way. DotA 2 is one of the most played games with over eight million unique users per month (2014-06-27) (Valve 2014). DotA 2 is also very e-sports friendly, the game is free and professional games can be observed inside the game client.

1.3 OUTLINE OF THE THESIS

Chapter 2 will give an introduction to all different metrics that were used and some processing of data. Chapter 3 will go through theory, results and conclusions for linear regression to try and fit a model to the data. Chapter 4 will go through theory, results and conclusions for using support vector machines to try and separate better player from less good players. Chapter 5 will discuss the results and the different methods used and chapter 6 will go through conclusions and discuss any possible future work.
METRICS

In order to get a visual attention index, Tobii REX eye trackers were distributed to DotA 2 players of different skill levels. The test persons played games of DotA 2 while using the eye tracker and software that measured where the test persons were looking during the game. In order to get a number for the player’s visual attention different metrics were used as measures. In this project, a metric is something that is connected to a player’s visual attention and that can be measured, for example the frequency of how often a player looked at a region on the screen.

2.1 AREAS OF INTEREST

The DotA 2 in game screen can be classified into different regions or Areas Of Interest (AOIs). After discussion with test subjects and professional gamers, some AOIs were chosen, the chosen AOIs are visualized in Figure 2.

2.1.1 Minimap

The minimap is the small map in the bottom left of the screen (highlighted with green in Figure 2). Everything that happens in the game (where your team has vision) can be observed on the minimap. If the player keeps track on the minimap he/she can detect incoming danger and be able to avoid it in time.

2.1.2 Abilities

Abilities is the region in the bottom middle of the screen (highlighted with red in Figure 2). When you use an ability, that ability cannot be used again for some time, it can be important to keep track on that time.

2.1.3 Items

Items are located in the bottom right corner (highlighted in yellow). Some items have active properties with cooldowns and some items
Figure 2: A screenshot taken from DotA 2, AOIs have been highlighted.

expire after a time period, therefore it might be important to keep track on the items.

2.1.4  *Mana/Hp*

Mana/Hp is in the bottom middle of the screen, above abilities (highlighted with blue in the picture). It displays how many health points and mana points the players hero has left. When a hero’s health points drop to zero, that hero dies. Abilities cost mana and therefore it might be important to keep track on the mana bar as well.

2.1.5  *Clock*

Clock is located in the top middle (highlighted in teal). There are different events happening in the game connected to the game time and therefore it might be important to keep track on the clock.

2.1.6  *World*

World is located in the middle of the screen, it is the largest AOI, the game board where most of the action takes place.

2.2  **FIXATIONS**

Fixation is the state when the eye is still for a while, for example when the eye temporarily stops at a word during reading. Fixations can last from tens of milliseconds up to several seconds. Fixations can be used to measure attention to a position (Holmqvist et al. 2011).
2.3 Visits

<table>
<thead>
<tr>
<th>From:</th>
<th>To:</th>
<th>Minimap</th>
<th>Abilities</th>
<th>Items</th>
<th>Mana/HP</th>
<th>Clock</th>
<th>World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimap</td>
<td>-</td>
<td>10 %</td>
<td>5 %</td>
<td>2 %</td>
<td>15 %</td>
<td>50 %</td>
<td></td>
</tr>
<tr>
<td>Abilities</td>
<td>20 %</td>
<td>-</td>
<td>10 %</td>
<td>25 %</td>
<td>2 %</td>
<td>40 %</td>
<td></td>
</tr>
<tr>
<td>Items</td>
<td>10 %</td>
<td>15 %</td>
<td>-</td>
<td>10 %</td>
<td>2 %</td>
<td>45 %</td>
<td></td>
</tr>
<tr>
<td>Mana/HP</td>
<td>15 %</td>
<td>20 %</td>
<td>10 %</td>
<td>-</td>
<td>2 %</td>
<td>40 %</td>
<td></td>
</tr>
<tr>
<td>Clock</td>
<td>5 %</td>
<td>2 %</td>
<td>2 %</td>
<td>5 %</td>
<td>-</td>
<td>70 %</td>
<td></td>
</tr>
<tr>
<td>World</td>
<td>20 %</td>
<td>15 %</td>
<td>15 %</td>
<td>10 %</td>
<td>5 %</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Visit Transition Matrix (numbers are made up)

2.3 Visits

If a player has consecutive fixations in an AOI (there are no fixations in another AOI in between the fixations), the fixations are merged into a visit (one fixation without any consecutive fixations in the same AOI will also count as a visit). The visit time is the time from the start time of the first fixation in the AOI to the stop time of the last (consecutive) one. Visit frequency and mean visit time for different AOIs were used as metrics. A transition matrix over the visits were also used, the transition matrix is a matrix that has info about how many percent of the time the user has changed region from one region to another. The transition matrix is visualized in Table 1

2.4 Used Metrics

The metrics used were:

1. Fixations per minute - average number of fixations per minute during a game
2. Mean Fixation Length - average fixation length during a game
3. Region Change Per Minute - average number of region changes per minute during a game
4. Mean Minimap Visit Time - average minimap visit time during a game
5. Mean Items Visit Time - average items visit time during a game
6. Mean Abilities Visit Time - average abilities visit time during a game
7. Mean Mana/Hp Bar Visit Time - average fixation mana/hp bar visit time during a game
8. Minimap Visit Per Minute - average number of minimap visits per minute during a game
9. Items Visit Per Minute - average number of minimap visits per minute during a game
10. Abilities Visit Per Minute - average number of minimap visits per minute during a game
11. Mana/Hp Visit Per Minute - average number of mana/hp bar visits per minute during a game
12. Clock Visit Per Minute - average number of clock visits per minute during a game
13. Region Change Not To World - average number of region changes not to world region per minute during a game

These metrics can also be seen in table 2.

2.5 VISUAL ATTENTION AND RANKING

Since the visual attention of a player is not measurable, the ranking of the player is used to estimate the visual attention of the player. It is assumed that a player of a higher ranking has a better visual attention than a player with lower ranking, this might not always be the case since the ranking is a kind of measurement of skill which is dependent on a lot of factors and a player of lower ranking might have a better visual attention than a player of higher ranking but lack in other factors. However, a person of a higher ranking should in general (with many players) have a better visual attention. A reason to use player ranking to estimate the visual attention of a player is that there already exists a ranking inside DotA 2 which is measurable. That ranking is called Match Making Rating (MMR).

2.6 MATCH MAKING RATING

DotA 2 has a match making system that assigns a rank to every player that no one can see, however, after playing enough games, “Ranked Matchmaking” is unlocked. In Ranked Matchmaking every player gets a ranking, which the player and the player’s friends can see. When players search for games they are matched with people of similar Match Making Rating (MMR), the winning team will have their average MMR increased and the losing team will have their average MMR decreased (Valve 2014b). The MMR for the test persons was used to measure their ranking.

2.7 COEFFICIENT OF CORRELATION

The coefficient of correlation, \( \frac{\text{Cov}[X,Y]}{\sqrt{\text{Var}[X] \cdot \text{Var}[Y]} } \), was calculated for the MMR with every metric respectively. From the transition matrix it was
Table 2: Coefficient of correlation between metric and MMR

<table>
<thead>
<tr>
<th>Metric</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixations per minute</td>
<td>-0.0349</td>
</tr>
<tr>
<td>Mean Fixation Length</td>
<td>-0.3625</td>
</tr>
<tr>
<td>Region Change Per Minute</td>
<td>0.5040</td>
</tr>
<tr>
<td>Mean Minimap Visit Time</td>
<td>-0.3334</td>
</tr>
<tr>
<td>Mean Items Visit Time</td>
<td>-0.1868</td>
</tr>
<tr>
<td>Mean Abilities Visit Time</td>
<td>-0.0424</td>
</tr>
<tr>
<td>Mean Mana/Hp Bar Visit Time</td>
<td>-0.0068</td>
</tr>
<tr>
<td>Minimap Visit Per Minute</td>
<td>0.2993</td>
</tr>
<tr>
<td>Items Visit Per Minute</td>
<td>0.4582</td>
</tr>
<tr>
<td>Abilities Visit Per Minute</td>
<td>0.3754</td>
</tr>
<tr>
<td>Mana/Hp Visit Per Minute</td>
<td>0.1822</td>
</tr>
<tr>
<td>Clock Visit Per Minute</td>
<td>0.0579</td>
</tr>
<tr>
<td>Region Change Not To World</td>
<td>0.5068</td>
</tr>
</tbody>
</table>

found that transitions from the minimap to other regions than world had a much higher correlation with the MMR than average and transition from minimap to world had a stronger negative correlation than average. From this knowledge a new metric was created: the percentage of all transitions from all regions except world to all regions except world (called "Region Change Not To World"). This metric showed an even stronger correlation with MMR. The coefficient of correlation for all metrics used are shown in table 2. Worth noting is that all metrics measured in time seems to be negatively correlated with the MMR while all metrics measured in $t^{-1}$ (except one) seems to be positively correlated with MMR.

2.8 PROCESSING OF DATA

15 Tobii REX eye trackers were distributed to test persons, however, only 7 test persons played sufficiently enough games for the data to be valid.

2.8.1 Plotting single metrics against MMR

The different metrics were plotted against the MMR of the test person for all games to investigate correlations between the metrics and MMR and also to get a picture of metrics that might be important. An example of one metric plotted versus the MMR is shown in Figure 3. From these plots non-linear relationships might be observed as well.
Figure 3: Minimap visits per minute, every point represents a match. The data points in this figure are unfiltered.

Figure 4: Minimap visits per minute, every point represents a match. The data points in this figure are filtered.
2.8 Processing of Data

2.8.2 Data Preprocessing

When observing the data, there appeared some outliers: some of the data points differed a lot from the other data points in several metrics. When inspecting the data files for the outliers, there were two major causes for this: Either there were a lot of data points that were positioned wrong (outside of the screen) or there were gaps where there were no gaze points registered. To handle this, two measures were taken, the frequency of the tracker was 30 Hz, if there were less than 20 gaze points per second (20 Hz) registered on average, that match was ignored. If there were more than ten percent of the gaze points registered outside of the screen, that match was also ignored. To improve the quality of the data further some measures were taken. If the data was good enough to pass the criterion above but there were some time jumps and points outside the screen, those points were removed. If there were more than 300 milliseconds between two gaze points, the time between them was removed from the total time. If there where gaze points outside the screen, those points were also removed and if there were less than three points between a point outside the screen and the next point outside the screen, all points in between were removed and the time in between was removed from the total time. As seen in Figure 5 there are times where there are no gaze points at all and some gaze points are outside of the screen (resolution of the screen was 1920x1080). The filtering can be seen in the difference between figure 3 (unfiltered) versus figure 4 (filtered).
Figure 5: Gaze points (*) and fixations (.) plotted over game time, y coordinates are blue and x coordinates are red, from this graph it can be seen that there are big time gaps with no data and gaze points which are outside the boundaries of the screen.
LINEAR REGRESSION

In order to get a number which reflects the players visual attention index, the first method used was linear regression. In order to verify if some metrics are relevant, hypothesis testing can be used, in this project the hypothesis tests T-test and F-test were used.

3.1 LINEAR REGRESSION

A linear regression is performed for predicting a quantitative response $Y$ based on either one or several predictors $X_1, X_2, ..., X_p$. The multiple linear regression model has the form

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + ... + \beta_pX_p + \epsilon,$$  \hspace{1cm} (1)

Given the estimates $\hat{\beta}_0, \hat{\beta}_1, ..., \hat{\beta}_p$ of the coefficients $\beta_0, \beta_1, ..., \beta_p$ the response, $\hat{y}$ can be predicted by

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1x_1 + ... + \hat{\beta}_px_p$$  \hspace{1cm} (2)

where the parameters $\beta_0, \beta_1, ..., \beta_p$ are estimated using the least squares method (James et al. [2013]). In this study, the different $X_i$ will be the metrics used (e.g. $X_p =$ minimap visits per minute) and $Y$ will be the MMR of the player. In the ordinary case the response, $Y$, is seen as a random variable but in this study, the different variables, $X_1, X_2, ..., X_p$, are seen as random variables. Therefore, this is not a standard linear regression and might not yield correct results, but it is easy to perform a linear regression and therefore, trying to do a linear regression is a logical first step.

3.2 T-TEST

The t-test is conducted to test the null hypothesis $H_0$: there is no relationship between the response and the predictor (only for one predictor). The standard error of the estimated coefficient ($\hat{\beta}_1$) is used to determine how far away from zero $\hat{\beta}_1$ is, if the standard error is large then the absolute value of $\hat{\beta}_1$ needs to be large in order to exclude
that $\hat{\beta}_1 \neq 0$. In order to determine if $\hat{\beta}_1 \neq 0$, a t-statistic is computed (SE($\hat{\beta}$) is the standard error of $\hat{\beta}$):

$$t = \frac{\hat{\beta}_1 - 0}{SE(\hat{\beta}_1)}$$

(3)

The $t$-statistic measures the number of standard deviations that $\hat{\beta}_1$ is away from zero. If there is no relationship between the response and the predictor, the $t$-statistic is expected to have a t-distribution with $n - 2$ degrees of freedom. Assuming $\beta_1 = 0$, the probability of observing any value equal to or larger than $|t|$ is calculated. This probability is called p-value. The p-value can roughly be interpreted as: a small p-value indicates that it is unlikely to observe an association between the predictor and the response due to chance, if there is no real association between the predictor and the response. Hence, a small p-value infers that there is an association between the predictor and the response. If the p-value is small enough, the null hypothesis is rejected—that is, a relationship is declared to exist between the predictor and the response. Typical p-value cutoffs for rejecting the null hypothesis are 5 or 1 % (James et al. 2013).

### 3.3 F-TEST

The F-test is used in multiple regression ($Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_p x_p + \epsilon$). The F-test is conducted to test the null hypothesis $H_0$: $\beta_1 = \beta_2 = ... = \beta_p = 0$. To test the hypothesis $H_0$, the F-statistic is calculated:

$$F = \frac{(TSS - RSS)/p}{RSS/(n - p - 1)}$$

(4)

Where $TSS = \sum_{i=1}^{n} (y_i - \bar{y})^2$ and $RSS = \sum_{i=1}^{n} (y_i - \hat{y})^2$, $n$ is the number of data points, $p$ is the number of predictors, $y_i$ is an observed value of the response, $\bar{y}$ is the estimated mean of the response ($\frac{1}{n} \sum_{i=1}^{n} y_i$) and $\hat{y}_i$ is the calculated value of the corresponding response $y_i$.

If $H_0$ is true, then the F-statistic will take on a value close to one. If $H_0$ is not true, then the F-statistic will take on a value greater than one, hence, if the F-statistic is large enough, $H_0$ can be rejected. How large the F-statistic needs to be to reject $H_0$ depends on the value of $n$ and $p$. When $H_0$ is true and the errors $\epsilon_i$ follows a normal distribution, the F-statistics follows an F-distribution. Using this distribution, a p-value can be calculated. If the p-value is sufficiently small, $H_0$ is rejected, that is, at least one of the predictors is associated with the response. (James et al. 2013)
3.4 Quality of the Regression

To measure the quality of the regression, different measures can be used. The Residual Standard Error (RSE = \sqrt{\frac{1}{n-p-1}RSS}) which measures how well the model fits the data, a better model will have a lower RSE. The \( R^2 \) statistic (\( R^2 = \frac{TSS-RSS}{TSS}, 0 \leq R^2 \leq 1 \)) measures the proportion of the variance explained by the regression, a better model will have an \( R^2 \) value closer to one. When adding more predictors, the \( R^2 \) value will increase, therefore the adjusted \( R^2 \) value (adjusted \( R^2 = 1 - \frac{RSS/(n-p-1)}{TSS/(n-1)} \)) can be used to determine the quality of the model (James et al. 2013).

3.5 Results

In this section, the results from the linear regression can be found. A multilinear fit was made using the metrics: mean fixation length (in milliseconds), fixations per minute, visits per minute and mean visit length (in seconds) to the regions minimap, abilities, items, mana/hp and clock, number of region changes per minute, percentage of all region changes not to world. When doing this regression, it is assumed that every match from every player can be counted as independent, that is, that all matches for each player are treated as if they were played by different players with the same MMR. Furthermore it is assumed that the errors are normally distributed which might not be the case (James et al. 2013). Even though there are very bold assumptions, it is still natural to try the linear fit and see if anything useful comes from it. The function \textit{lmfit} in MATLAB was used to get all values for the fitting constants. To get the most relevant metrics, variable selection was used, specifically the backward selection method was used to remove metrics that is least statistically significant. A t-test is conducted for all metrics and the metric with the highest p-value is removed, a new linear model is then fit without the removed metric and a new t-test is conducted. This procedure was repeated until the p-values of all metrics where less than 5 percent (James et al. 2013). The remaining metrics and the equation used are shown in Equation 5 and the statistics for the coefficients are shown in Table 3.

\[
\hat{\beta}_0 + \hat{\beta}_1 \cdot \text{[Fixations Per Minute]} + \\
+ \hat{\beta}_2 \cdot \text{[Mean Fixation Length]} + \hat{\beta}_3 \cdot \text{[Region Change Per Minute]} + \\
+ \hat{\beta}_4 \cdot \text{[Mean Minimap Visit Time]} + \hat{\beta}_5 \cdot \text{[Minimap Visits Per Minute]} + \\
+ \hat{\beta}_6 \cdot \text{[Items Visit Per Minute]} + \hat{\beta}_7 \cdot \text{[Region Change Not to World]}
\]  

(5)
### Table 3: Backward selection method

Another method was also used, the best subset selection method. Every combination of predictors is fitted using an algorithm, if there are a total of \( p \) predictors then:

1. Start with the null model (no predictors).
2. For \( k = 1, 2, ..., p \)
   - Fit all the \( \binom{p}{k} \) models and choose the best one (the model with smallest \( \text{RSS} \) or largest \( R^2 \))
3. Select the best model of all \( p + 1 \) models using cross validated prediction error, \( C_p \) (AIC), BIC or adjusted \( R^2 \), in this project, adjusted \( R^2 \) was used.

\cite{James2013}

The results are shown in table 4, metrics used are shown in equation (6)

\[
\hat{\beta}_0 + \hat{\beta}_1 \cdot \text{[Fixations Per Minute]} + \hat{\beta}_2 \cdot \text{[Mean Fixation Length]} + \\
+ \hat{\beta}_3 \cdot \text{[Region Change Per Minute]} + \hat{\beta}_4 \cdot \text{[Mean Minimap Visit Time]} + \\
+ \hat{\beta}_5 \cdot \text{[Minimap Visits Per Minute]} + \hat{\beta}_6 \cdot \text{[Items Visit Per Minute]} + \\
+ \hat{\beta}_7 \cdot \text{[Region Change Not to World]} + \hat{\beta}_8 \cdot \text{[Clock Visit Per Minute]}
\]

An interesting note is that in both regressions, the constant belonging to Region Change Per Minute is negative even though the coefficient of correlation between Region Change Per Minute and the MMR was positive. Region Change Per Minute might be positively correlated with the MMR when used alone, but in this case Region Change Per Minute is compared for players with the same number for the other metrics used in the regressions (it might be bad for players to have a higher Region Change Per Minute when players have...
Table 4: Best subset selection result

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Standard Error</th>
<th>t-Statistic</th>
<th>pValue</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\beta}_0$</td>
<td>6172.7</td>
<td>846.21</td>
<td>7.2945</td>
</tr>
<tr>
<td>$\hat{\beta}_1$</td>
<td>-9.842</td>
<td>4.7974</td>
<td>-2.0515</td>
</tr>
<tr>
<td>$\hat{\beta}_2$</td>
<td>-2.5932</td>
<td>1.2179</td>
<td>-2.1291</td>
</tr>
<tr>
<td>$\hat{\beta}_3$</td>
<td>-1833.7</td>
<td>835.51</td>
<td>-2.1947</td>
</tr>
<tr>
<td>$\hat{\beta}_4$</td>
<td>-1239.6</td>
<td>238.43</td>
<td>-5.1989</td>
</tr>
<tr>
<td>$\hat{\beta}_5$</td>
<td>97.966</td>
<td>25.552</td>
<td>3.834</td>
</tr>
<tr>
<td>$\hat{\beta}_6$</td>
<td>151.05</td>
<td>46.155</td>
<td>3.2726</td>
</tr>
<tr>
<td>$\hat{\beta}_7$</td>
<td>4881</td>
<td>1185</td>
<td>4.1188</td>
</tr>
<tr>
<td>$\hat{\beta}_8$</td>
<td>538.71</td>
<td>434.2</td>
<td>1.2407</td>
</tr>
</tbody>
</table>

$R^2 = 0.612$  
adj $R^2 = 0.579$  
F-statistic = 18.5  
pValue = 2.24 $\cdot 10^{-16}$

Linear regression was a natural first step, however, it turned out that the results were not that good at predicting the MMR of a player. Linear regression may yield good results if there are a lot more data from more players, but with the data obtained in this study, linear
Figure 6: Every * corresponds to the MMR of a player (X axis) and calculated VAI (using equation 6) for a match of the same player (Y axis)
Figure 7: Every * corresponds to the MMR of a player (X axis) and calculated VAI for a match of the same player (Y axis). The calculated VAI is calculated using cross validation.
regression did not yield a good model for predicting the visual attention. After this discovery, another method was needed, a method that did not need a lot of conditions to hold and that could separate the players. This led to the use of Support Vector Machines (SVM).
Another method to try and find differences between players at different skill levels is to use support vector machines (SVMs), it is a way to classify data into two classes [Cortes & Vapnik 1995].

4.1 MAXIMAL MARGIN CLASSIFIER

Hyperplanes can be used to separate two different classes. In a p-dimensional space, a hyperplane is a translated subspace of dimension p-1, defined by: \( w \cdot x - b = 0 \). If a point satisfies \( w \cdot x - b = 0 \) then the point lies on the hyperplane. If a point does not satisfy \( w \cdot x - b = 0 \) then either \( w \cdot x - b > 0 \) and the point lies on one side of the plane or \( w \cdot x - b < 0 \) and the point lies on the other side. If the Data points are linearly separable, then there are two hyperplanes with no data points in between that will separate the two classes. Those hyperplanes can be described by: \( w \cdot x - b = 1 \) and \( w \cdot x - b = -1 \), where \( w \cdot x - b \geq 1 \) for one class and \( w \cdot x - b \leq -1 \) for the other class, the distance between the planes is \( \frac{2}{||w||} \) [Cortes & Vapnik 1995]. After some rearrangements in the variables, this leads to the following optimization problem in the variables \( w \) and \( b \):

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2}||w||^2 \\
\text{subject to} & \quad w \cdot h_i - b \geq 1 \\
& \quad w \cdot s_j - b \leq -1
\end{align*}
\]

Where \( h_i = \{x_i| x_i \in \text{class one}\} \) and \( s_j = \{x_j| x_j \in \text{class two}\} \)

However, the two classes might not be linearly separable, or there might be some points that violate the margin. This can be handled by introducing slack variables \( \xi_1, \xi_2, ..., \xi_n \) which measure the error of every data point, and this is penalized in the optimization problem:
\[
\min_{w,b} \frac{1}{2}||w||^2 + C \sum_{i=1}^{n} \xi_i \\
\text{subject to} \\
w \cdot h_i - b \geq 1 - \xi_i \\
w \cdot s_j - b \leq -1 + \xi_j \\
\xi_i \geq 0.
\]

Where C is a tuning parameter that has to be chosen from problem to problem (Cortes & Vapnik 1995).

4.2 RESULTS FOR THE ABOVE CLASSIFIER

All hyperplanes were calculated in an attempt to separate better players (players with an MMR greater than 4000) from not as good players (players with an MMR less than 4000). At first, hyperplanes were calculated using combinations of two metrics (chosen based on the value of the coefficient of correlation) with two different values of C, the results are plotted in figure 8, each point corresponds to one match by one player. From these plots it can be seen that a higher value of C appears to give a better separation of the points due to the optimization problem giving less of weight to individual points. Therefore a higher value of C was used in the calculations (C=100).

Hyperplanes were calculated for all combinations of three metrics. The procedure to evaluate the metrics was for every player i:

1. Exclude the data points from player i
2. Calculate the hyperplanes.
3. Add the data points from player i and calculate the percentage of points that are misclassified by the hyperplane (points on the wrong side).

When these quotes have been calculated for all players, take the mean of all quotes. This mean was used to compare all different combination of three metrics. The combination of metrics that had the lowest quotient can be seen in figure 9. With the metrics skills visit per minute, items visit per minute and fixation per minute the percentage of number of points on the wrong side of the hyperplane is shown in table 5.

4.3 AN ALTERNATIVE METHOD OF SEPARATION QUALITY

In this section an alternative method, suggested by Svanberg (2015), for measuring the quality of a separation hyperplane is used. It is based on distances from all points to the hyperplane \( w \cdot x = b \). If
4.3 AN ALTERNATIVE METHOD OF SEPARATION QUALITY

Figure 8: Hyperplane for different pair of metrics calculated with different values on C
Figure 9: Hyperplane based on the three metrics with least number of cross border points
4.4 The Quotient Method for Calculating the Hyperplane

Another approach, suggested by Svanberg (2015), is to use the quotient \( \theta \) to optimize the hyperplane. This method will lead to a linear optimization problem with one extra constraints included. Since \( d_k^- \)
and $d_k^+$ is the absolute distance we know that $d_k^- \geq 0$ and $d_k^+ \geq 0$ which means that $\sum_k d_k^+ \geq 0$ and $\sum_k d_k^- \geq 0$. Furthermore, $\sum_k d_k^- = 0$ if and only if there is a hyperplane that perfectly separates the points and $\sum_k d_k^+ = 0$ if and only if there is no point which is strictly on the correct side of the plane, neither of these two alternatives is the case in this study, therefore we can assume that $\sum_k d_k^+ > 0$ and $\sum_k d_k^- < 0$.

(If there is a single point on the right side and not on the hyperplane, then $d_k^+ > 0$ for that point and $\sum_k d_k^+ > 0$, if there is only points on the wrong side, then there will be a better plane that separates the classes, for example the plane identical to the former but the classes switch places.)

If $\sum_k d_k^+ > 0$ and $\sum_k d_k^- < 0$ then $\theta > 0$ and minimizing $\theta$ is equivalent to maximize $1/\theta$ and also equivalent to maximizing $1/\theta - 1$, since adding a constant will not change the outcome of the optimization.

$$1/\theta - 1 = \frac{\sum_k d_k^+}{\sum_k d_k} - 1 = \frac{\sum_k d_k^+ - \sum_k d_k^-}{\sum_k d_k} \cdot \frac{\sum_k d_k}{\sum_k d_k}$$

By similar arguments as above, we may assume that $\sum_k d_k > 0$. Then maximizing $\sum_k d_k$ is equivalent to minimizing $\sum_k d_k^-$. An advantage with minimizing this quotient is that the quotient will be independent of the scaling of $w$ and $b$. If $w' = t \cdot w$ and $b' = t \cdot b$ is used, then

$$d_i' = w' \cdot h_i - b' = t \cdot w \cdot h_i - t \cdot b = t \cdot (w \cdot h_i - b) = t \cdot d_i$$
$$d_j' = \{ \text{In the same way} \} = t \cdot d_j$$
$$d_k^+ = \max \{ d_i', 0 \} = \max \{ t \cdot d_i + 0 \} = t \cdot \max \{ d_i, 0 \} = t \cdot d_i^+.$$  
$$d_k^- = \{ \text{In the same way} \} = t \cdot d_i^-.$$  

and

$$\frac{\sum_k d_k^-}{\sum_k d_k} = \frac{\sum_k t \cdot d_k^-}{\sum_k t \cdot d_k} = \frac{t \cdot \sum_k d_k^-}{t \cdot \sum_k d_k} = \frac{\sum_k d_k^-}{\sum_k d_k}$$

This means that for any $t \neq 0$, $w' = t \cdot w$ and $b' = t \cdot b$ will solve the same optimization problem as $w$ and $b$. This leads to the conclusion that $\sum_k d_k$ can be set to a constant, $\sum_k d_k = T(T > 0)$, and the objective function will not change.

$$\min_{\sum_k d_k} \frac{\sum_k d_k^-}{\sum_k d_k} \iff \min_{\sum_k d_k = T} \frac{\sum_k d_k^-}{T} \text{ subject to } \sum_k d_k = T$$

$$\iff \min_{\sum_k d_k} \frac{\sum_k d_k^-}{\sum_k d_k} \text{ subject to } \sum_k d_k = T$$

If each $d_k^-$ in class one is represented by a variable $\eta_i$, and each $d_k^-$ in class two is represented by a variable $\nu_i$, the following optimization problem is obtained:
4.5 Comparison between hyperplane methods

When performing these two different optimizations (Soft Margin and Quotient-method), it is interesting to compare the two methods. This comparison was performed in the case with two metrics as well as three metrics. The five best combinations of metrics are shown in

\begin{align*}
\text{minimize} & \quad \sum_i \eta_i + \sum_j \nu_j \\
\text{subject to} & \\
\eta_i & \geq -w \cdot h_i + b \\
\nu_j & \geq w \cdot s_j - b \\
\eta_i & \geq 0, \nu_j \geq 0 \\
\sum_i (w \cdot h_i - b) - \sum_j (w \cdot s_j - b) & = T
\end{align*}

The result of solving this optimization problem is shown in figure 10 with the quotient $\theta = 0.0480$ and when calculating the hyperplanes with cross validation $\theta = 0.0513$. 

Figure 10: Hyperplane based on the three metrics with lowest quotient $\theta$
Table 6: The top five combination of two metrics using the soft margin method and sorting by mean cross border points (in percent)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Cross Border [%]</th>
<th>Quotient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mean minimap visit time, Region change not to world</td>
<td>15.08</td>
<td>0.0726</td>
</tr>
<tr>
<td>2. Mean items visit time, Items visit per minute</td>
<td>16.07</td>
<td>0.1171</td>
</tr>
<tr>
<td>3. Items visit per minute, Skills visit per minute</td>
<td>16.96</td>
<td>0.0951</td>
</tr>
<tr>
<td>4. Mean fixation length, Items visit per minute</td>
<td>17.33</td>
<td>0.1051</td>
</tr>
<tr>
<td>5. Items visit per minute, Region change not to world</td>
<td>17.54</td>
<td>0.0865</td>
</tr>
</tbody>
</table>

As can be seen in tables 6 to 9, many of the top one to five metrics combinations are the same with the soft margin method as well as the quotient method.
### Table 7: The top five combination of two metrics using the quotient method and sorting by mean quotient

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Cross Border [%]</th>
<th>Quotient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mean minimap visit time, Region change not to world</td>
<td>14.56</td>
<td>0.0701</td>
</tr>
<tr>
<td>2. Region change per minute, Region change not to world</td>
<td>20.77</td>
<td>0.0854</td>
</tr>
<tr>
<td>3. Items visit per minute, Region change not to world</td>
<td>16.93</td>
<td>0.0867</td>
</tr>
<tr>
<td>4. Items visit per minute, Skills visit per minute</td>
<td>16.81</td>
<td>0.0890</td>
</tr>
<tr>
<td>5. Mean fixation length, Items visit per minute</td>
<td>17.81</td>
<td>0.0895</td>
</tr>
</tbody>
</table>

### Table 8: The top five combination of three metrics using the soft margin method and sorting by mean cross boarder points (in percent)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Cross Border [%]</th>
<th>Quotient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Fixations per minute, Items visit per minute, Skills visit per minute</td>
<td>12.18</td>
<td>0.0603</td>
</tr>
<tr>
<td>2. Fixations per minute, Mean minimap visit time, Region change not to world</td>
<td>12.74</td>
<td>0.0734</td>
</tr>
<tr>
<td>3. Mean minimap visit time, Mean mana hp bar time, Region change not to world</td>
<td>12.89</td>
<td>0.0662</td>
</tr>
<tr>
<td>4. Mean minimap visit time, Items visit per minute, Region change not to world</td>
<td>13.35</td>
<td>0.0761</td>
</tr>
<tr>
<td>5. Mean items visit time, Items visit per minute, Skills visit per minute</td>
<td>14.18</td>
<td>0.0954</td>
</tr>
</tbody>
</table>
Figure 11: Hyperplane for different pair of metrics calculated with different values on C and the quotient method
### Table 9: The top five combination of three metrics using the quotient method and sorting by mean quotient

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Cross Border [%]</th>
<th>Quotient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mean minimap visit time, Mean mana hp bar visit time, Region change not to world</td>
<td>15.19</td>
<td>0.0518</td>
</tr>
<tr>
<td>2. Fixations per minute, Items visit per minute, Skills visit per minute</td>
<td>15.85</td>
<td>0.0650</td>
</tr>
<tr>
<td>3. Region change per minute, Mean minimap visit time, Region change not to world</td>
<td>13.85</td>
<td>0.0663</td>
</tr>
<tr>
<td>4. Fixations per minute, Mean minimap visit time, Region change not to world</td>
<td>11.91</td>
<td>0.0675</td>
</tr>
<tr>
<td>5. Mean minimap visit time, Skills visit per minute, Region change not to world</td>
<td>13.99</td>
<td>0.0680</td>
</tr>
</tbody>
</table>
DISCUSSION

In this chapter, the results will be discussed and analyzed.

5.1 MMR

When a fit is made, it is assumed that player of higher MMR have better visual attention than a player with a lower MMR. While the MMR is used as a measure of a players overall skill, the overall skill of the player probably depends on different parameters as well, meaning that a player with better visual attention might have a lower MMR than another player because that player is stronger in some other aspects (e.g. game mechanics). This effect should cancel out when the number of players is large, which is not the case in this study.

5.2 PLOTTING METRICS

Plotting the metrics gave a picture of metrics that might be important (as seen in section 2.8.1), however, since the number of metrics were large, looking at all the plots was not very perspicuous. This way, however, might be the easiest way to discover non-linear relationships.

5.3 COEFFICIENT OF CORRELATION

Calculating the coefficient of correlation between the metrics was a natural way to see which metrics that were relevant by only looking at metrics with an absolute value of the correlation with the MMR that was higher than some limit. This yielded that merging some of the metrics seemed like a good idea. The drawback of looking at the coefficient of correlation is that it does not give any information about correlation with other metrics.

5.4 MULTILINEAR FIT

The multilinear fit with the backward selection method proved to be an effective way to get relevant metrics and values on the fitting
discuss**

**Discussion**

This method also takes different importance of different metrics into account, just because one metric can have a high correlation with the MMR alone, does not mean that it has a significant importance in contrast to the other metrics. The multilinear fit does not take nonlinear terms into account and there might be nonlinear relations between the MMR and the visual attention. The multilinear fit also has conditions that have to be fulfilled which might not be the case, but even so, the multilinear fit can be used to see if something good comes out of it. In this study, there was not much of value that came out of the multilinear fit, other than showing that it is not suitable to use this method on this specific collection of data.

5.5 Data Preprocessing

Data errors was a problem. Since there were only data from seven people, every individual player will have a high impact on the results. The test person with the highest MMR had a lot of noisy data, the data was so noisy that the fixation filter had a hard time finding fixations which lead to that the player with the highest MMR had very low fixations per minute. When performing the multilinear fit this made having higher fixations per minute have a negative impact on the visual attention index which sounds counter-intuitive (higher fixations per minute could imply that the player has processed more information, leading to a higher MMR).

5.6 Support Vector Machine

Using support vector machines was an effective way to find relevant metrics by seeing how good the data points from better players can be split from points from players that are not as good. An advantage with this approach is that there are no assumptions that have to hold and it is quite fast for a computer to calculate the hyperplanes. The difficulty in using Support Vector Machines was to find a good measure of what is a better metric. Since there are many points that are crossing the margin, the margin will not be a very reliable measure of good metrics. The percentage of all points on the wrong side of the hyperplane was a better measure of the metrics used, since it will compare all combination of metrics in the same way. The quotient (sum of all distances on the wrong side over sum of all correct distances from the hyperplane) is similar to comparing percentage of points on the wrong side but it also takes into consideration how far the points are crossing the border. The quotient had the plus side that it could, with some modifications, be used as target function in the optimization. An interesting note from figure 11 is that the hyperplane from the quotient method seems to be very similar to the hyperplane from the soft margin method for higher values of C, this
is most likely because a higher value of C will punish points crossing the border more and the quotient method is optimizing with respect to the distance to those cross boarder points, which makes them similar. When checking tables 6 to 9 it is also noticeable that a lot of the combinations of metrics occurs in tables for both methods, this is good since it verifies that those metrics are good (since the metrics comes up in two different methods.)
CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

Since there were only seven people actually using the equipment sufficiently enough, the results from this study will not be statistically significant, however, the results can be used as guide lines of what metrics that might be good and the developed procedure can be applied when more data is collected.

6.1.1 multilinear fit

The results of the fit combined with conversation with professional DotA 2-players led to the conclusion that metrics that probably will be good to use as variables are: Mean minimap visit time, minimap visits per minute, items visits per minute and region change not to world. To find more relevant metrics, and to get good estimates of coefficients, more data has to be collected.

6.1.2 Support vector machine

Using hyperplanes to separate better players from other players was an effective way to find relevant metrics. The quotient method had the upsides of being able to directly compare the target function to the target function of other metrics. That both hyperplane methods yields similar results in which metrics that are best separating the players is also good, since it says which metrics are good in two different ways. The three metrics that best separates the two better players from the five others in this study is mean minimap visit time, mean mana/hp bar visit time and region change not to world.

6.2 FUTURE WORK

The main future work will be collecting more data to get a better model. There are also some other aspects that has not been taken into account in this project, the possibility of a non-linear model can also be considered.
6.2.1 Game Events

The metrics used in this study has just concerned averages over entire games. In the future it might be interesting to look at some of the metrics connected to a certain time point, e.g. a team fight (when many heroes fight each other together with team members) or when the player’s hero is dead. Another interesting metric might be the number of observed events, e.g. enemy obtaining new items, players missing from the map that might be on the way to attack someone. To do this, info over different events has to be gathered somehow.

6.2.2 Roles

In DotA 2 the five players can take on different roles (since it is a team game), the different roles typically do different things, and hence the look pattern of players might differ depending on which role they play. A way to find which role the player is playing also has to be developed in order to investigate how roles affect the visual attention.

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