Self-breakthrough is the Greatest

Summary

Sports are loved and praised by people. The spirit of self-improvement is the excellent quality of each player. We think players achievement self-breakthrough based on good performance is the "greatest". Therefore, what players have achieved and how much they have improved is the core clue to understanding our G.O.A.T. model.

Based on the Elo algorithm, we propose the ranking score model (RSM). RSM considers the factors and variables such as the current strength of players, the expectation of winning, the level of competition, the round of the competition, the game performance and the state of the competitors, etc. to ensure the fairness and reliability when updating the ranking scores. One of the highlights of the RSM is that we consider the player's game performance parameter P, which can give rewards (if player performs well) or punishment (if player performs badly) when updating ranking scores based on the results of each round of games. Based on RSM, we also propose a progress model (PM), which is a measure of the player's "self-breakthrough" level. Combined with RSM and PM, we established a comprehensive evaluation model (CEM). The CEM's results show that the greatest woman tennis player of 2018 is Simona Halep.

By changing the score updating method in RSM, we make the model consider the cumulative ranking score over time, and upgrade CME to G.O.A.T. model. The model takes snooker as an example of individual sport to test. We collected relevant data of five competitions (World Championships, UK Championships, Shanghai Masters, China Open and Welsh Open) from 2007 to 2017. The G.O.A.T. model shows that Mark Selby is the G.O.A.T. of snooker (2007-2017 period).

It's very easy to extend our G.O.A.T. model to any individual sport. We introduce in detail the parameters that need to be changed in the model and the personalized configuration method for different sports. All the expansion work can be summarized into three steps. First, in RSM, the initial ranking score should be reassigned. Second, redefine the game performance parameter P. Thirdly, considering the influence of player status on fairness, the model can be modified appropriately.

We introduce how to extend our G.O.A.T. model to team sports, and take basketball as an example to discuss in detail.

The data used by the model are public and we have referenced them in the corresponding locations. We put the collected data, model results, notations, relevant code and model evaluation in Attachment.

Keywords: Elo algorithm, ranking score model, progress model, comprehensive model

Contents

1. Introduction

1.1 Restatement of the Problem

Backgrounds: Through history, sports have been highly praised by people, and the Olympic Games once every four years has become one of the oldest traditional competition. Sports can help people build up and keep fit, but more, the spirit of indomitable struggle affects people's values in a deeper level, which guides people in a positive and upward direction. A sports superstar must have special characteristics (e.g. winning the most awards or breaking the world record), worthy of people's praise and learning.

After determining the "greatest", we need to build a mathematical model based on the results of the competition and other data to complete the following tasks:

- Develop a model to determine the greatest woman tennis player in 2018.
- Choose one example of an individual sport and develop a model to determine the G.O.A.T.
- Consider any changes the model would require. of any individual sport and temp sport.
- Write to Director who understands little about math, and report our results.

1.2 Our Work

First, we make it clear how do we define "the greatest". We construct a Ranking Score Model (RSM) based on Elo algorithm. We use the Seed/Rank information of woman players to define their initial score, and consider the score update algorithm from the competition level, round, game performance, player status and other factors, so as to make the model use the existing data as much as possible and become fair. In addition, we propose a Progress Model (PM) to measure the degree of self-breakthrough of players. Based on the above two models, we construct a Comprehensive Evaluation Model (CEM), which will help us determine who is the greatest. The CEM shows that the greatest woman tennis player of 2018 is Simona Halep and we analyze the results of the model solution. All of above will be introduced in Section 3.

In Section 4, we chose snooker as an example of model testing and we collected the data of five competitions from 2007 to 2017. We consider the cumulative change of ranking scores over time based on RSM, and choose new factors to add to build our G.O.A.T. model. The results show that Ding Junhui is the G.O.A.T. of snooker (2007-2017 period). We analyze the results and show how to extend the G.O.A.T. model to any individual sport in three steps.

Section 5 briefly introduces the general method of extending the G.O.A.T. model to team sports. In Section 6, the advantages and problems of our model are discussed. In addition, we show two new ideas to improve the model. Section 7 is the letter we sent to the Director.

2. Model Assumptions

1. (Strength equilibrium) It is assumed that the difference between players‘ ranking score decreases with the increase of ranking.
2. It is assumed that the player's expectation of winning obeys the normal distribution.
3. It is assumed that four tennis tournaments have the same level.

3. Comprehensive Evaluation Model

First, we make it clear how do we define "the greatest". In our model, athletes achieve self-breakthrough based on good performance is the "greatest". Therefore, we divide the model into two parts: ranking score model (RSM) and progress model (PM). The former will give the ranking according to the athlete's competition performance and other data, while the latter will evaluate the progress according to the changes of ranking score before and after the competition. based on the results of the above two parts, we propose a comprehensive evaluation model.

The modeling process of the Section 3 is shown in Fig 1.

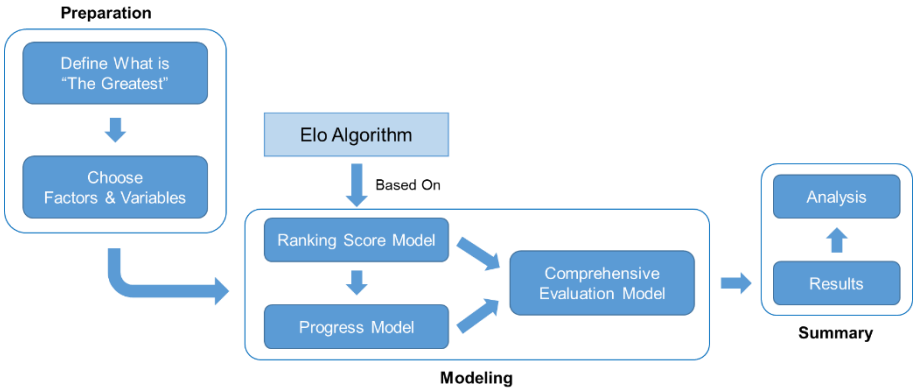

Fig 1: The modeling process of Section 3

3.1 Ranking Score Model (RSM)

In 1960, physicist Arpad Elo proposed an evaluation algorithm named Elo to measure the level of various tournament [1]. The Elo algorithm is one of the core methods for evaluating the level of the tournament, and it is widely used in chess, Go, football, basketball, e-sports and other sports. Based on the core principles of the Elo algorithm, we will comprehensively consider the current strength of the players, player status, game performance, wins and losses, victory expectation, schedule weights and other variables to propose a new RSM. Our model contains more tournament information and can represent the strength of players more fairly and objectively.

3.1.1 Elo Algorithm

We will introduce the main idea of the Elo algorithm. Take the chess game as an example. Suppose the current ranking scores of player A and player B are R_A, R_B, respectively. The Elo algorithm assumes that the player's expectation of winning follows the Logistic distribution. Then player A and player B's expectation of winning E_A, E_B, are respectively:

$$E_A = \frac{1}{1+e^{\frac{(R_B-R_A)}{N}}}. \tag{3.1}$$

$$E_B = \frac{1}{1+e^{\frac{(R_A - R_B)}{N}}} = 1 - E_A . \tag{3.2}$$

In the above two formulas, N is a scaling factor, which makes the value of expectation more evenly distributed in the interval $(0,1)$. $N = 400$ in a chess game. Assuming that the score of player A in the game is W_A ($W_A = 1$, $W_A = 0.5$, $W_A = 0$ respectively corresponds to victory, draw and defeat), the ranking score of player A after the game $\overline{R_A}$ uses formula (3.3) to update,

$$\overline{R_A} = R_A + H \cdot (S_A - E_A), \tag{3.3}$$

Among them, H is a limit value, which represents the score and loss value of at most one player theoretically can win, and $H/2$ is the score obtained by one of the players with the same ranking score. $H = 16$ in the chess masters; $H = 32$ in most games. H is also the weight of the game level. In general, the higher the level of the game, the lower the H value. The reason for this setting is to avoid changing the ranking of top players in a few games.

3.1.2 Our Choice of Factors and Variables

From the result data of the four competitions (2018 Grand Slam Results), we extracted four model parameters of the player's current strength, player status, game performance, wins and losses. We will discuss the definition and properties of these model parameters separately.

(a) The current strength (Seed/Rank)

To update the ranking score based on the Elo algorithm, we first assign an initial value to the ranking score of each player, and the variable Seed/Rank can be used to complete this work. According to the description of Seed/Rank in the appendices, we can make a preliminary estimate of the player's strength from the value of Seed/Rank.

For seeded players, the higher their ranking, the stronger their current strength, and the maximum ranking is 32. This part of the player is the strongest among all the contestants. We can add a ranking score to each seeded player based on the basic score, and the higher the ranking, the more points will be added. According to the assumption of strength balance, we let the score difference between players gradually decrease as the seeded ranking increases.

For PR, Q and Blank players, we set the strength of PR to be stronger than Q. Since Blank players did not provide any information about their strengths, their strength ranked last. We will assign different initial values to players in these three states in the order of PQ > R > Blank .

Finally, for players in Seed/PR status, they have very strong strength, and their previous rankings are very high, but because they were inactive recently, their seeded ranking has dropped. Therefore, we can think that their real ranking should be higher than the value of Seed/PR. We will use the same assignment formula as seed players to assign initial values to the ranking scores of Seed/PR players, but their Seed/Rank will be appropriately improved.

In summary, we use formula (3.4) to define the ranking score R, which measures the player's current strength, as follows:

$$R=\begin{cases}1000 & \text{Blank},\\ 1100 & \text{Q},\\ 1150 & \text{PR},\\ 1200+\text{Round}(100\times\ln[4\cdot(33-\text{seed}/2)-11]) & \text{Seed/Rank},\\ 1200+\text{Round}(100\times\ln[4\cdot(33-c\cdot\text{seed}/2)-11]) & \text{Seed/PR}.\end{cases} \tag{3.4}$$

In formula (3.4), we set a minimum score of 1000 for people in Blank state. This is to avoid negative numbers in subsequent score updates. The variable seed is the seeded ranking, and c is the Seed/PR promotion coefficient. In our model, $c=0.75$ (i.e. if the real seeded ranking of Seed/PR players should increase by 75%). We use the logarithmic function to assign the initial ranking scores of the seeded players. The logarithmic function can well satisfy the difference between the players and gradually decrease as the seeded ranking increases. For seed players, the setting of some coefficients in the initial value function can make the initial ranking scores more evenly distributed in the interval $(1200,1500)$. $\text{Round}(\cdot)$ is the rounding function.

(b) The player status

We have observed that players in the PR state will not be able to complete the game normally, which will allow the opponent to win directly. We use an indicative function χ_{PR} to describe whether there are players with PR status in a game, so as to modify the update of the ranking score in this case in the model. The definition of χ_{PR} is as follows:

$$\chi_{\text{PR}}=\begin{cases}0 & \text{No one is in PR in the game},\\ 1 & \text{Someone is in PR in the game}.\end{cases} \tag{3.5}$$

(c) The game performance

We use the parameter P to measure the performance of two players in a game, and discuss it in two parts. In each match, women play to win two out of three sets. We set an incentive coefficient p_0 based on the result of the tournament, and p_0 is defined as follows:

$$p_0=\begin{cases}1.25 & \text{Won the game by 2:0},\\ 1 & \text{Won the game by 2:1},\\ 0.75 & \text{Lost the game by 1:2},\\ 1 & \text{Lost the game by 0:2}.\end{cases} \tag{3.6}$$

In formula (3.6), we have made the following settings: when a player wins the game 2:0 (i.e. "gain a complete victory"), $p_0=1.25$ will be used as an incentive coefficient to increase the effect of ranking points; The player loses the game 1:2 (i.e. "go down swinging"), $p_0=0.75$ will be used as the incentive coefficient to reduce the ranking score reduction effect. Discussing p_0 separately is abstract. If combined with the RSM in Section 3.1.3, the meaning of parameter p_0 will be more specific and easier to understand.

In addition, we can also use the scores of each segment in a round to calculate the player's game performance P_i. In the section without tiebreaker, we assume that the greater the difference between the two players, the greater the difference in performance ratings. P_i is defined as follows:

$$P_i = \frac{1}{2} + \frac{1}{1+e^{(-1)^{W_i}\cdot\frac{|\Delta_i|}{2}}}, \tag{3.7}$$

in which, W_i represents the win-loss situation of the current section, $W_i = 1$ means victory, and $W_i = 0$ means defeat. $|\Delta_i|$ is the difference in scoring between the two players in the current section. From the definition, $P_i \in (0.5, 1.5)$ can be obtained. If $W_i = 1$, then $P_i > 1$, and the larger the score difference $|\Delta_i|$, the closer P_i is to 1.5, the higher the game performance score; if $W_i = 0$, then $P_i < 1$, and the greater the difference $|\Delta_i|$, The closer P_i is to 0.5, the lower the game performance score.

In the section with tiebreaker, we still use the same idea of formula (3.7) to calculate P_i with the difference of the deciding game, but we reduce the impact of the score difference (because the total score of this section is 6:7, This shows that in this section, the performance of the two players is equal), P_i in the case of a tiebreaker is defined as follows:

$$P_i = \frac{1}{2} + \frac{1}{1+e^{(-1)^{W_i}\cdot\frac{|\Delta_i|}{10}}}, \tag{3.8}$$

Finally, we combine p_0 and P_i to define the game performance P of each round:

$$P = p_0 \cdot \text{mean}\left(\sum\nolimits_i P_i\right), \tag{3.9}$$

in which, $\text{mean}(\cdot)$ is the mean function.

(d) wins and losses

We use W to represent the wins and losses of each round of competition. It will form a reward and punishment model together with the expectation of winning. The definition of W is as follows:

$$W = \begin{cases} 1 & \text{This round won,} \\ 0 & \text{This round was defeated.} \end{cases} \tag{3.10}$$

3.1.3 The Model for Updating Ranking Score

Based on the core idea of the Elo algorithm (3.3) and comprehensively considering the various factors and variables mentioned above, we constructed a model for updating the ranking score of Player A after each section of tournament as follows:

$$\overline{R_A} = R_A + \text{Round}(H \cdot C_k \cdot P \cdot (W - E_A) \cdot (1 - \chi_{PR}) \cdot S) \tag{3.11}$$

Among them, R_A represents the ranking score of player A before each section of tournament. The initial value can be calculated using formula (3.4), and $\overline{R_A}$ represents the score after the tournament (after update). H is the weight of the tournament level, the higher the level of the tournament, the smaller the H. In our model, we assume that the four championships in 2018 in the given data have the same level, and all set $H=16$.

C_k represents the weight of each tournament round. We are given different weights for the matches between the top 16, the top 8, and the top 4 and the finals. Like H, the closer to the final, the smaller the value of C_k, in order to prevent a few games from changing the ranking of top players. The provided data is recorded starting from the top 16, so we set 4 different weights C_k to correspond to the four rounds, as shown in Table 1.

Table 1: The weight C_k of each tournament round

k	Explanation	C_k
1	Fourth Round (competition between the top 16)	4
2	Quarterfinals (competition between the top 8)	2
3	Semifinals (competition between the top 4)	1
4	Final (competition between the top 2)	0.5

P represents the in-game performance score, which is calculated by formula (3.9). W represents the outcome of each section of tournament, E_A is A's expectation of winning against player B, which is a probability value in the interval $(0,1)$. Here we assume that the probability of A winning against B is independent and identically distributed, and its density function is $p(x)$, the function $p(x)>0$ and $p(x)$ has a continuous derivative function. Under the assumption of power balance, we set $p(x)$ to be symmetric about $x=0.5$, and the average value of the sample will maximize the likelihood function. Gauss derived the expression of probability density $p(x)$ based on the above conditions in the early 19th century, which is the well-known Gauss distribution [2]. Now, under the assumption of normal distribution, we set the variance $\sigma^2=1$, and define the expectation E_A for A to win against B as:

$$E_A=\frac{1}{2}+\int_0^{\frac{R_A-R_B}{N}}\frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}\mathrm{d}x \tag{3.12}$$

R_A, R_B are the current ranking scores of players A, B, and N is the scaling factor, which can make the expected E_A more evenly distributed in the interval $(0,1)$. We take $N=400$.

In the formula (3.11), χ_{PR} represents the PR status judgment function. It can be seen that when one of the two contestants is in the PR status, the ranking scores of the two players will not be updated, which reflects the fairness of the tournament. Finally, the parameter S represents the player's promotion status. If the player is eliminated in a certain round, $S=0$ is set after that. The model will determine the state S at the beginning, if $S=0$, the score will not be updated. $\mathrm{Round}(\cdot)$ is the rounding function.

Combined with the analysis of the various parameters of the model, the model will increase the ranking score when the player wins, and deduct the ranking score when the player loses. The game performance P measures the competitive situation of each person in each round of the game, and will zoom in (or zoom out) to add extra points (or deductions) $W - E_A$.

It must also be pointed out that the model (3.11) can be used to calculate the ranking scores of each player after each tournament. However, the 16 players in each tournament in the data are different, and the initial ranking of the seeded players at the beginning of the tournament will also change. In this question, we do not consider the cumulative change of player ranking scores over time. Therefore, at the beginning of each tournament, we re-assign the initial ranking scores of the 16 players based on the Seed/Rank status.

Let $R_A^{(WC)}$, $R_A^{(FO)}$, $R_A^{(US)}$, $R_A^{(AO)}$ respectively indicate that player A is the last in the Wimbledon Championships, French Open, US Open, and Australian Open. The ranking scores obtained, and the average of the four scores are used to represent their overall ranking scores in 2018 (the non-participating competitions are not scored, so they will not be counted as the average). The 2018 average ranking scores of 39 female tennis players were obtained by solving the model. Table 2 shows the scores of the top 10 players (see Attachment 1 for complete data).

Table 2; The ranking scores of the top 10 players

Name	2018 Wimbledon Championships	2018 French Open	2018 US Open	2018 Australian Open	Average Score in 2018
S Halep	N	1574	N	1546	1560.00
S Stephens	N	1518	1515	N	1516.50
G Muguruza	N	1514	N	N	1514.00
C Wozniacki	N	1457	N	1552	1504.50
Ka Pliskova	1426	N	1479	1484	1463.00
J Ostapenko	1462	N	N	N	1462.00
E Svitolina	N	N	1433	1489	1461.00
J Gorges	1459	N	N	N	1459.00
A Kerber	1519	1464	N	1392	1458.33
M Keys	N	1460	1464	1421	1448.33

(N means that the player did not participate in the tournament in 2018)

3.2 Progress Model (PM)

After obtaining the change data of the players' ranking scores in each competition, we can consider the progress of each player in each tournament $P_A^{(tournament)}$, in the formula (3.13), We use the percentage of the post-match score change to the initial score to calculate the progress

$$P_A^{(\text{tournament})} = \frac{R_A^{(\text{tournament})} - R_A^0}{R_A^0} \times 100\%, \tag{3.13}$$

in, which, R_A^0 represents the initial ranking score of player A in the tournament. Next, add up the progress of player A in each tournament, and get the total PM P_A as:

$$P_A = P_A^{(WC)} + P_A^{(FO)} + P_A^{(US)} + P_A^{(AO)}. \tag{3.14}$$

Using (3.14), the 2018 progress scores of a total of 39 woman tennis players were calculated. Table 3 shows the progress of the top 10 players (see Attachment 2 for complete data).

Table 3: The progress of the top 10 players

Name	2018 Wimbledon Championships	2018 French Open	2018 US Open	2018 Australian Open	Total Progress in 2018
A Kerber	6.52%	3.24%	N	3.49%	13.26%
M Keys	N	3.47%	4.35%	3.05%	10.87%
S Halep	N	5.50%	N	3.62%	9.12%
S Williams	5.71%	0.00%	4.35%	-1.20%	8.87%
S Stephens	N	5.93%	2.36%	N	8.30%
C Suarez Navarro	N	N	3.26%	4.00%	7.26%
Y Putintseva	N	5.60%	N	N	5.60%
E Mertens	N	-1.22%	-1.43%	8.00%	5.34%
A Sevastova	N	N	5.06%	N	5.06%
C Giorgi	4.50%	N	N	N	4.50%

(N means that the player did not participate in the tournament in 2018)

3.3 Comprehensive Evaluation Model (CEM)

Both the RSM (3.11) and the PM (3.14) characterize the strength of players, and the larger the value of both, the better. For a rookie tennis player, because there is no record of winning, the initial ranking score is low, but she defeats multiple opponents continuously with her excellent performance, and gets higher ranking points. Although the ranking score is not noticeable, we must acknowledge the progress she has made. When using it, we also need to pay attention: In our model, top players are more difficult to make progress than rookies in tennis (because in the model (3.14), top players have a larger denominator R_A^0. At the same time, In the model (3.11), the top players have a relatively large winning probability E_A, so the bonus item $W - E_A$ obtained is relatively small, so that $R_A^{(tournament)}$ is relatively small).

We draw a scatter plot of the ranking R_{RSM} of the RSM and the ranking R_{PM} of the PM as shown in Fig 2. According to the previous analysis, we hope that the larger the values of the two models, the better, i.e. the higher the ranking R_{RSM}, R_{PM}, the better (in Fig 2, the closer the point represented by the player is to the origin, the better).

We consider using the linear combination of R_{RSM}, R_{PM} as a comprehensive index to evaluate the "greatest" degree of athletes, and define the CEM as follows:

$$CE = \lambda \cdot R_{\mathrm{RSM}} + (1-\lambda) \cdot R_{\mathrm{PM}} \tag{3.15}$$

In formula (3.15), the parameter $\lambda \in [0,1]$ is the weight parameter of the CEM. When $\lambda = 1$, it means that we only evaluate whether the player is "the greatest" from the RSM (only paying attention to the ranking score and ignoring the self-breakthrough achieved by the player is contrary to our definition of "the greatest"); When $\lambda = 0$, we will use the PM as the only criterion to measure the players (but it is unrealistic to only focus on progress and ignore the impressive results achieved by the players). Here, we will pay more attention to their self-breakthroughs based on the players' impressive results, and set the parameter $\lambda = 0.60$.

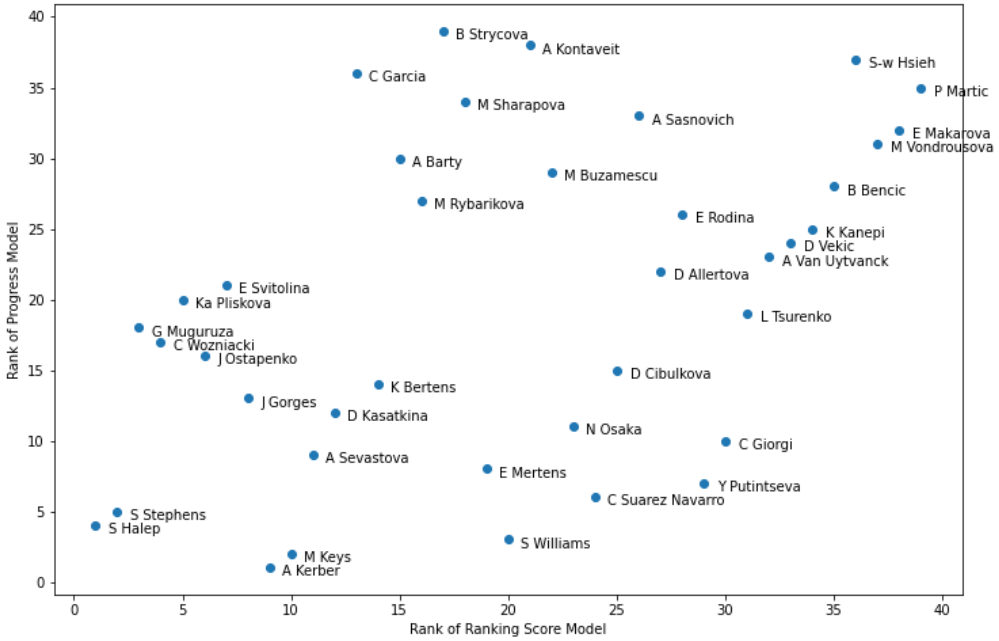

Fig 2: Scatter plot of R_{RSM} and R_{PM}

(In the figure, the players near the lower left corner have high RSM and PM rankings.
In the comprehensive evaluation model, they are the "greatest")

3.4 The Greatest Woman Tennis Player of 2018

Using the model (3.15), the 2018 comprehensive ranking of a total of 39 female tennis players was calculated. Table 4 presents the comprehensive scores of the top 10 players (see Attachment 3 for complete data). Now, we can conclude: the greatest woman tennis player of 2018 is Simona Halep.

Analyzing the results in Table 4, we can conclude:

(a) The greatest female tennis player in 2018 is Simona Halep. Simona Halep ranked first in the two tournaments she participated in (2018 French Open and 2018 Australian Open), and she eventually won the 2018 French Open champion and the 2018 Australian Open runner-up. Considering Simona Halep's game performance, we can find that in most games, she can win the game with a large point difference. The extremely high initial ranking points and the extraordinary performance of breaking through the self-have given the title of "Greatest" well-deserved.

(b) Angelique Kerber, the number one player in the PM, participated in 3 games in 2018 (2018 Wimbledon Championships, 2018 French Open and 2018 Australian Open), and her initial seed ranking is about 20. But in three championships, Angelique Kerber won a championship, once entered the semi-finals, once entered the quarter-finals (lost to the first place Simona Halep in the quarter-finals), from the statistics we can see Angelique Kerber's self-breakthrough, so she ranked third in the comprehensive evaluation algorithm.

(c) Serena Williams participated in 3 games in 2018 (2018 Wimbledon Championships, 2018 French Open and 2018 US Open). She was in a special PR status in 2018 French Open and 25/PR status in 2018 Wimbledon Championships, which made her ranking score in the algorithm is greatly reduced. However, her real strength should be higher than the current ranking. She has reached the finals twice in the three tournaments (and in the 2018 French Open she was unable to compete due to physical reasons). Even if affected by injuries, we can see from the data that Serena Williams is still strong, surpassing herself, and returning to the top performance, which makes her ranked fifth in the CEM.

(d) Most of the top R_{PM} athletes have achieved good results in the comprehensive algorithm, and some athletes (such as Julia Gorges, Caroline Wozniacki, and Jelena Ostapenko) rank among the top 10 in the comprehensive model with high ranking scores.

Table 4: The comprehensive scores of the top 10 players

Name	R_{RSM}	R_{PM}	CE	Final Ranking
S Halep	1	4	2.8	1
S Stephens	2	5	3.8	2
A Kerber	9	1	4.2	3
M Keys	10	2	5.2	4
S Williams	20	3	9.8	5
A Sevastova	11	9	9.8	6
J Gorges	8	13	11	7
C Wozniacki	4	17	11.8	8
D Kasatkina	12	12	12	9
J Ostapenko	6	16	12	10

4. Extend the Model to Determine G.O.A.T.

The comprehensive evaluation model in Section 3.3 only considers the performance of the athletes in one year. To determine the G.O.A.T. of a certain sport, we need to measure the performance of the players over a long period of time, but our core idea will not change, that is, self-breakthrough is "the greatest". We will consider the cumulative change of the score over time based on the RSM (3.11). In this way, the final score of a player is no longer simply an average of the ranking scores of all competitions. In addition, compared to tennis, other sports have a different scoring mechanism (or have more evaluation indicators), which will change the definition of the game performance parameter P in the model (3.11). We choose snooker as an example to test our algorithm.

The modeling process of the Section 4 is shown in Fig 3.

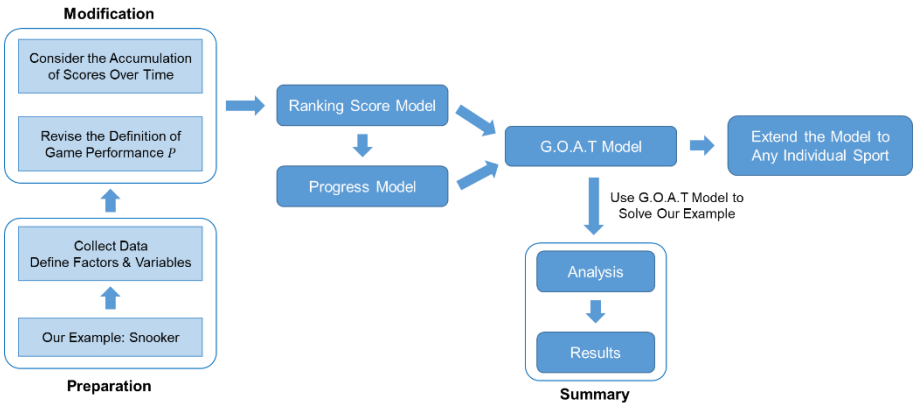

Fig 3: The modeling process of Section 4

4.1 Our Example: Snooker

We choose snooker as the example to test the G.O.A.T. model. Snooker's scoring rules in the game are very different from those of tennis, and we have selected some other indicators to add to the calculation of the RSM. In addition, the new model will consider the cumulative changes in scores over time. We will separately introduce the collection of snooker game data, the modifications made to the model, and the analysis of the solution results of our G.O.A.T model.

4.1.1 Data Description

We collected data [3] on five tournaments from 2007 to 2017. They are the World Championship, UK Championship, Shanghai Masters, Welsh Open and China Open. There are no small rounds in each round of snooker, and as the rounds increase, the competition system will change (generally, the later the round, the more wins are needed to win the game, and different rounds will use such as win 5 out of 9 sets, 6 out of 11 sets,10 out of 19 sets, etc.).

We collected the world rankings of all players at the end of 2006 as the basis for the score initialization in the RSM. In addition, in addition to the game score, we will also use the other two indicators in the snooker game to participate in the calculation of the athlete's performance in the game. They are whether a single stroke breaks the 100 (that is, the score exceeds 100 in a single stroke) and whether to get a perfect score (that is, 147 points in a single stroke), we believe that these are two important indicators for evaluating the strength of snooker players. Fig 4 shows the score record of the 2013 World Championship. Each record separately records the player's world ranking, name, score in the current round, the number of times a single stroke breaks 100 in this round, and the number of full scores in a single stroke in this round. All the snooker competition data we collected can be found in Attachment 4.

54	M White	13	3	0
87	D Poomjaeng	3	0	0

15	R Walden	13	2	0
36	R Milkins	11	3	0

2	J Trump	13	2	0
28	M Fu	7	0	0

9	R O'Sullivan	13	2	0
17	A Carter	8	2	0

6	S Murphy	13	2	0
13	G Dott	11	3	0

11	D Junhui	13	3	0
31	M King	9	1	0

22	B Hawkins	13	4	0
1	M Selby	10	2	0

16	S Bingham	13	3	0
19	M Davis	10	4	0

15	Ricky Walden	13	2	0
54	Michael White	6	0	0

2	Judd Trump	13	3	0
6	Shaun Murphy	12	2	0

9	Ronnie O'Sullivan	13	2	0
16	Stuart Bingham	4	0	0

22	Barry Hawkins	13	2	0
11	Ding Junhui	7	0	0

9	Ronnie O'Sullivan	17	6	0
2	Judd Trump	11	3	0

22	Barry Hawkins	17	5	0
15	Ricky Walden	14	6	0

9	Ronnie O'Sullivan	18	8	0
22	Barry Hawkins	12	5	0

Fig 4: The score record of the 2013 World Championship

4.1.2 G.O.A.T. Model

We will obtain the G.O.A.T. model by changing the RSM on the basis of the comprehensive evaluation model (3.15). The core difference of the new algorithm is twofold. On the one hand, the ranking score update formula (3.11) needs to be accumulated over time; on the other hand, the player's game performance P (i.e. formula (3.9)) needs to be redefined according to the new scoring mechanism and newly added variables.

(a) Update of ranking scores

When determining the greatest female tennis player of 2018, we did not distinguish the order of the four tournaments. Instead, we used the player's status information to give them a new initial ranking score at the beginning of each game. The scores are updated independently for each tournament, and finally the average score of all games is counted as the final score.

In the new model, we also first consider the assignment of initial ranking scores. We collected a total of 103 snooker players' world rankings $Rank_0$ at the end of 2006 (if there is no ranking, $Rank_0$ is recorded as Blank), using the same idea as equation (3.4), we get the ranking score the initial value calculation formula (4.1) is as follows:

$$R=\begin{cases}1000 & Rank_0=\text{Blank},\\ 1000+\text{Round}(10^3\times\ln[4\cdot(94-Rank_0/2)-100]-4400) & Rank_0\neq\text{Blank}.\end{cases} \tag{4.1}$$

For each tournament, we basically use the formula (4.11) to update the ranking score of each player after the competition:

$$\overline{R_A}=R_A+\text{Round}(H_k\cdot C_k\cdot P\cdot(W-E_A)\cdot S) \tag{4.2}$$

The difference from the fourth quarter is that we need to sort the games according to the year (from 2007 to 2017) and the time of the five games each year. The ranking score after each comparison will be used as the initial score for the next game update, so that the ranking score will begin to accumulate over time, achieving a true "All Time".

In addition, the weight H_k of the tournament level in formula (4.2) is no longer fixed at $H=16$. For the five games we considered, according to the gold content of the games, we set the weights of the World Championships, UK Championships, and Shanghai Masters as $H_1=8$, and set the weights of the Welsh Open and China Open as $H_2=16$.

Since snooker players have no special status (PR in tennis matches, or Seed/PR), we have deleted the indicator function representing the PR status from (3.11).

(b) The redefinition of game performance P

In a tennis match, each section of the game generally has 2 to 3 bars (two wins in three games), and each bar needs to be counted. In the snooker game, every round is divided into sections, but we can still use the P_i defined in the formula (3.7) to calculate the game performance P_0 of the entire round based on the point difference:

$$P_0=\frac{1}{2}+\frac{1}{1+e^{(-1)^{W_i}\cdot\frac{|\Delta_i|}{\mu_i}}}, \tag{4.3}$$

in which, μ_i is the scaling factor, which allows P_0 to be more evenly distributed in the interval $(0.5,1.5)$. Since the snooker game changes with the rounds, the winning game system (i.e. the number of rounds required to win the game) will change, so μ_i is related to the number of winning rounds l_i required for the current round. We give a definition method for μ_i:

$$\mu_i=\sqrt{l_i}-1 \tag{4.4}$$

In formula (3.9), we also define an incentive coefficient p_0 (defined according to the win-loss situation in the three-game two-win system). The definition of p_0 does not apply in the snooker game. But we introduce two new parameters, p_1, p_2, which respectively represent the incentives brought by a single shot and a single shot. We use the Logistic function to define these two incentives:

$$p_1 = \frac{1}{2} + \frac{1}{1+e^{(-1)^{W_i}\cdot k_1}},\ p_2 = \frac{1}{2} + \frac{1}{1+e^{(-1)^{W_i}\cdot 2k_2}} \tag{4.5}$$

k_1, k_2 respectively represent the number of breaks in a single stroke and the number of perfect scores in a single stroke. Finally, combining P_0, p_1, p_2, we redefine the snooker game performance P as:

$$P = p_1 \cdot p_2 \cdot P_0 \tag{4.6}$$

It can be seen from formula (4.6) that when player A wins this game, the bigger the difference and the more times he breaks a hundred in a single stroke, it will get more points in the updated formula (3.11). When Player A loses in this game, combined with the definitions of p_1, p_2, the smaller the score difference, the more the number of breaks in a single stroke and the more perfect scores in a single stroke (indicating that the game performed well, but accidentally lost the game) will decrease. The points to be deducted in formula (3.11). If the score difference is large under the conditions of defeat, and there is no record of single-stroke breaking 100 and single-stroke full score, the algorithm will consider the game performance to be poor and deduct more ranking points from the updated formula (3.11).

The above are the changes in the G.O.A.T. model. At the end of 2017, we still use (3.13) to measure the progress of each athlete, and together with the ranking scores form a comprehensive evaluation model to determine the snooker G.O.A.T. (2007-2017 period)

4.1.3 The G.O.A.T. of Snooker

Using the G.O.A.T. model, the overall ranking of 103 snooker players from 2007 to 2017 was calculated. Table 5 presents the scores of the top 10 athletes (see Attachment 5 for complete data). Draw a scatter plot of the ranking R_{RSM} of the RSM and the ranking R_{PM} of the PM as shown in Fig 5 (only the top 30 athletes in the G.O.A.T model are shown). Now, we can conclude: the G.O.A.T. (2007-2017 period) of snooker is Mark Selby.

Analyzing the results in Table 5, we can get:

(a) In the RSM, Mark Selby's ranking rose from 9th to 2nd. From 2007 to 2017, Mark Selby entered the finals 15 times (9 times champion) and 25 times reached the semi-finals. His progress and breakthroughs are obvious to all. From 2007 to 2017, Snooker's G.O.A.T. was none other than him.

(b) The ranking of Ronnie O'Sullivan in RSM rose from the third to the first, and the ranking of Ding Junhui in RSM rose from the 27th to the third. They are ahead of the world rankings, meanwhile, they are also at the top of PM, which is very consistent with our definition of "Greatest", so Ronnie O'Sullivan and Ding Junhui are tied for second place.

(c) Comparing the solution results in Table 4 (Top 10 Women's Tennis Singles Comprehensive Score in 2018), we found that in the G.O.A.T. model, the players with the highest ranking in PM did not rank high in the comprehensive evaluation model. On the contrary, most of the top players in the G.O.A.T. model rank among the top in the RSM, and they also perform well in the PM. The above shows that when the G.O.A.T. model considers the accumulation

of ranking scores over time, the true "greatest" athletes should first accumulate extraordinary results (ranked among the best), and then continue to achieve self-breakthrough and transcendence.

Table 5: The top 10 snooker players in G.O.A.T. model

Name	R_{RSM}	R_{PM}	CE	G.O.A.T.
Mark Selby	2	2	1.6	1
Ronnie O'Sullivan	1	5	2.4	2
Ding Junhui	3	3	2.4	2
Stephen Maguire	4	8	4.8	4
Neil Robertson	6	9	6	5
Judd Trump	10	7	6.8	6
Ali Carter	8	10	7.2	7
Shaun Murphy	5	13	7.2	7
Mark Williams	7	12	7.6	9
Mark Allen	25	4	11.6	10

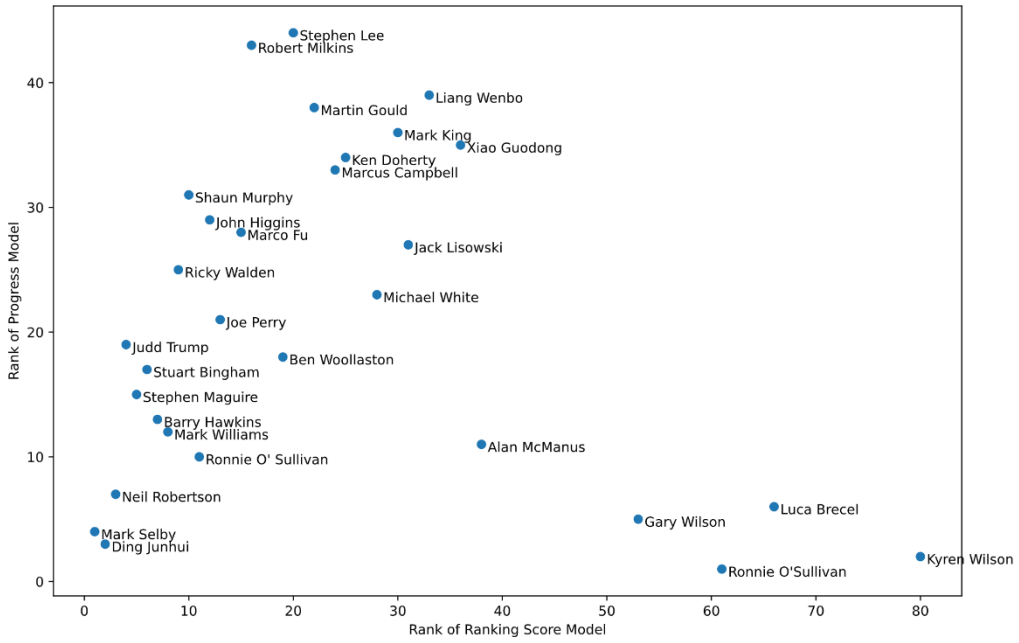

Fig 5: Scatter plot of R_{RSM} and R_{PM} (top 30 players in G.O.A.T. model)

4.2 Extend the G.O.A.T. Model to Any Individual Sport

It is easy to extend our G.O.A.T. model to any single-player sports. After determining the sport, there are generally three aspects of the model that need to be adjusted. First, adjust the players' initial ranking scores in the RSM according to the information they have mastered. Second, according to the characteristics of the game data, redefine the game performance P in the ranking score update formula (3.11). Third, examine the impact of player status on the fairness of ranking score updates and make appropriate adjustments. Next, we will explain these three tasks in more detail.

(a) Assignment of initial ranking scores

Before using the ranking score update formula, the current strength of the participating players must be evaluated and the initial ranking scores of each player must be assigned. This is an important basis for calculating winning expectations. There are many factors that can measure the strength of players. For example, in snooker we chose the current world ranking, while in the tennis match in the fourth quarter, we borrowed seeded rankings, qualifying matches and other information to assign values.

Under normal circumstances, we believe that the score difference between players should gradually decrease as the players' strength increases (this ensures that the information of subsequent matches will be better when updating scores, otherwise, the top players will be far away with extremely high score differences. Ahead of others). In addition, we believe that the initial score setting should be controlled within the interval $[1000, 2500]$. On the one hand, the lower limit of 1000 points ensures that no negative numbers appear when the score is updated. On the other hand, when the model uses the default parameters, the initial score in the range of $[1000, 2500]$ can make the proportion of the PM more gradual (generally no more than 15%).

(b) **Redefining game performance** P

Due to the different competition systems, scoring methods, and factors that determine the player's game performance, the definition of game performance P is relatively flexible. After determining the variables that can reflect the player's in-game performance, construct an index P that can objectively evaluate their performance. Since in the ranking score update model, points will be awarded for winning the game and points will be deducted for losing the game, and the game performance parameter P will be directly multiplied by the score change item $W - E_A$. For this reason, we need to ensure the parameter P has the following four properties:

- When a game wins, the better the player's performance is, the higher the P value should be, to get bonus points.
- When a game wins, the more ordinary the player's performance is, the lower the P value should be, not to receive additional rewards score.
- When a game fails, the better the player's performance, the lower the P value, to reduce the points that will be deducted for defeat.
- When a game fails, the worse the player's performance is, the higher the P value should be, so that P becomes a penalty.

Deduct more points. Taking the most common score difference Δ_i as an example as a variable to measure the performance P of the game, the Logistic function with the outcome of the win and loss W_i can well meet the above four properties, namely:

$$P = \frac{1}{2} + \frac{1}{1+e^{(-1)^{W_i}\cdot\frac{|\Delta_i|}{2}}} \tag{4.7}$$

(c) Investigate the impact of player status on fairness

Sometimes, players cannot complete the game due to physical reasons, but their participation information will be recorded in the game (such as PR status in women's tennis). In this case, the opponent will directly win the current round. At this time, we lack the game score information needed to calculate the score update, and it would become unfair to update the score directly. In order to solve this problem, we can consider adding an indicative function representing the player's state in the score update, for example, consider the formula (3.11):

$$\overline{R_A} = R_A + \text{Round}(H \cdot C_k \cdot P \cdot (W - E_A) \cdot (1 - \chi_{PR}) \cdot S) \tag{3.11}$$

We added the PR state function χ_{PR} to the score update. If one of the players is in the PR state, the score will not be updated (because there is no match between the two at all). The same idea can be extended to other individual sports to ensure the fairness of score updates.

To sum up, the Fig 6 shows how to extending the G.O.A.T. model to any sport.

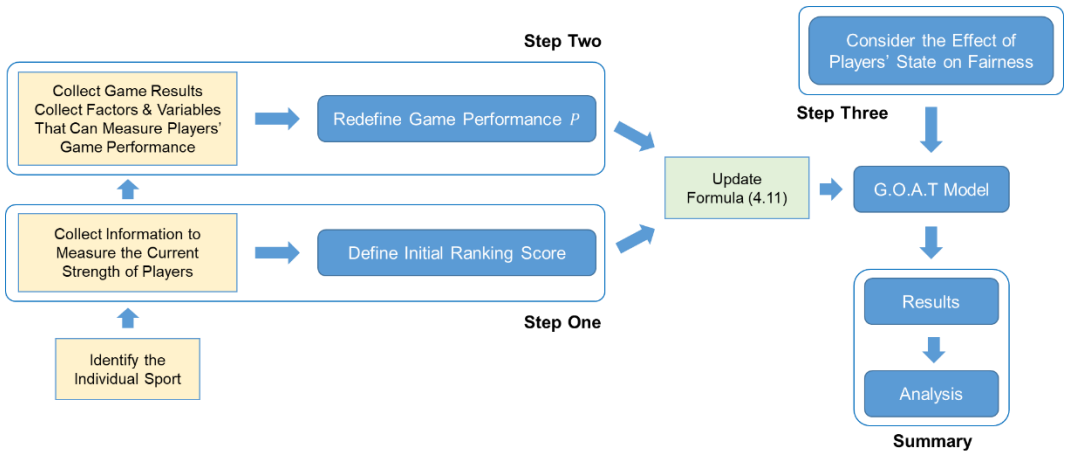

Fig 6: The method to extend the G.O.A.T. model to any individual sport

(Identify a sport and collect relevant information and data about the game.
There are three steps to adjust the parameters in G.O.A.T. model.
After getting the model, it is necessary to do model testing and analyze the results)

5. Extend the G.O.A.T. Model to Team Sport

In this section, we will extend the G.O.A.T. model to Team Sports and select NBA basketball players as the research group. As a collective sport, basketball is different from individual sports such as tennis and snooker in terms of competition methods and standards for measuring the ability of players. In response to the existing records of NBA player game data [4] and NBA basketball game rules, we have made some adjustments to the previous evaluation model of individual sports G.O.A.T.

First, the NBA has a special drafting mechanism. For players who are new to the league, the rounds in the draft represent their current strength and future development potential. Like the previous model, the rounds obtained by each player in the draft are quantified as the player's initial R_{pick} in the league. In each subsequent season, the player's performance point R_N will be added to the player's last season's final score. Next, explain in detail the composition of the performance points R_N during the season.

Different from individual sports, basketball games need to be completed in cooperation with other players. Therefore, in addition to selecting personal data and honors as one of the indicators for selecting G.O.A.T., players' contributions to the team are also an indispensable part. Here we introduce two concepts, Win Share (Wins) and Player Efficiency Rate (PER). Wins is used to measure the player's contribution to the team's victory at both the offensive and defensive ends (generally, the higher the WS value, the more important the player is to the team's victory), while PER considers the player's performance on the court. (Scores, rebounds, assists, steals, turnovers, etc.) are used to measure a player's efficiency value. The existence of this value allows players in different positions in different eras to be compared.

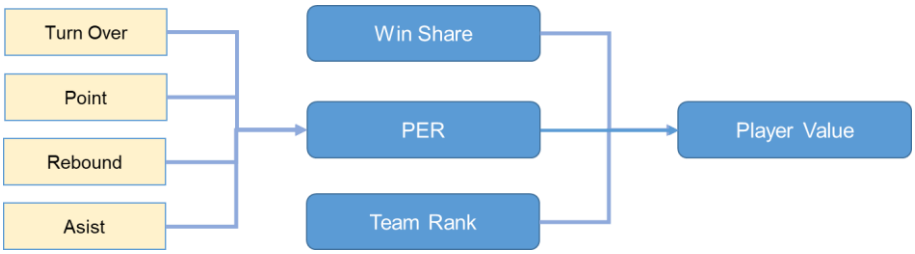

Fig 7: Factors contributing to player's value

A complete season can be divided into three stages: preseason, regular season, and playoffs. In the selection of G.O.A.T., we do not consider the performance of the players in the preseason.

In the regular season, the value of a player is not just about whether the personal data is good or not. The value of the data is largely determined by the team's record. We use the following formula to express the player's performance in the regular season:

$$R_0 = \frac{1}{1+e^{-k_0 \cdot r \cdot w_0 \cdot p_0}} \tag{5.1}$$

Among them, r represents the player's regular season record ranking points, the better the regular season record of the team, the greater the value of r; w_0 is the player's regular season Wins value; p_0 is the player's regular season PER value, k_0 is adjustable parameters. This design can fully consider the three factors of the player's team performance, personal victory contribution and personal efficiency, and filter out the outstanding personal PER value, but the team record is dismal, and the Wins value is not high. Karl-Anthony Towns in Fig 8 (source: [5]), his personal PER in the 2019-2020 season is as high as 26.5, ranking 7-th in the league, but his Wins value is only 5.1, which is the lowest of the top 10 PER. His Timberwolves team was only 14th in the West (second from the bottom) in the regular season. Therefore, only PER value, Wins value and team record are at a high level, the player's season performance points will be higher.

Advanced Share & Export ▾ When table is sorted, hide non-qualifiers for rate stats Glossary Show Partial Rows

Rk	Player	Pos	Age	Tm	G	MP	PER	TS%	3PAr	FTr	ORB%	DRB%	TRB%	AST%	STL%	BLK%	TOV%	USG%	OWS	DWS	WS	WS/48	OBPM	DBPM	BPM	VORP
1	Giannis Antetokounmpo	PF	25	MIL	63	1917	31.9	.613	.237	.508	7.7	34.8	22.1	34.2	1.5	3.0	13.2	37.5	6.1	5.0	11.1	.279	7.4	4.1	11.5	6.6
2	James Harden	SG	30	HOU	68	2483	29.1	.626	.557	.528	2.9	16.0	9.4	35.9	2.3	2.1	14.2	36.3	9.9	3.2	13.1	.254	8.1	1.6	9.6	7.3
3	Luka Dončić	PG	20	DAL	61	2047	27.6	.585	.431	.448	4.1	25.0	14.7	45.7	1.5	0.6	14.8	36.8	6.5	2.3	8.8	.207	7.4	1.0	8.4	5.4
4	Anthony Davis	PF	26	LAL	62	2131	27.4	.610	.199	.479	7.4	22.1	14.8	15.1	2.0	6.0	10.4	29.3	6.7	4.4	11.1	.250	5.4	2.6	8.0	5.4
5	Damian Lillard	PG	29	POR	66	2474	26.9	.627	.500	.384	1.4	10.5	6.0	34.4	1.3	0.8	11.0	30.3	10.9	0.7	11.6	.225	8.3	-0.9	7.5	5.9
6	Kawhi Leonard	SF	28	LAC	57	1848	26.9	.589	.287	.355	3.1	19.1	11.3	26.4	2.6	1.6	10.2	33.0	5.4	3.3	8.7	.226	6.5	2.4	8.9	5.1
7	Karl-Anthony Towns	C	24	MIN	35	1187	26.5	.642	.445	.363	8.1	26.1	16.8	22.8	1.3	2.9	13.2	28.8	3.7	1.3	5.1	.204	7.0	0.8	7.8	2.9
8	Joel Embiid	C	25	PHI	51	1506	25.8	.590	.215	.543	10.3	33.2	21.7	16.9	1.4	3.7	13.8	32.9	3.3	2.7	6.0	.192	3.7	1.0	4.7	2.5
9	LeBron James	PG	35	LAL	67	2316	25.5	.577	.326	.292	3.2	21.5	12.4	49.1	1.6	1.4	15.1	31.5	6.2	3.6	9.8	.204	6.6	1.8	8.4	6.1
10	Hassan Whiteside	C	30	POR	67	2008	25.0	.644	.010	.340	13.6	33.3	23.6	5.9	0.6	8.4	12.9	19.6	5.6	3.0	8.5	.204	2.5	0.7	3.2	2.6
11	Nikola Jokić	C	24	DEN	73	2336	24.9	.605	.238	.281	8.0	26.1	17.1	35.2	1.8	1.7	15.8	26.6	6.7	3.1	9.8	.202	5.5	2.0	7.4	5.5
12	Trae Young	PG	21	ATL	60	2120	23.9	.595	.455	.448	1.6	11.5	6.5	45.6	1.4	0.3	16.2	34.9	5.3	0.6	5.9	.133	6.2	-2.3	3.9	3.1
13	Jimmy Butler	SF	30	MIA	58	1959	23.6	.585	.157	.693	6.3	15.4	11.0	28.1	2.6	1.6	11.4	25.1	6.3	2.7	9.0	.221	4.0	1.5	5.4	3.7
14	Mitchell Robinson	C	21	NYK	61	1412	23.5	.726	.000	.434	13.7	18.8	16.2	3.9	1.8	8.0	8.3	13.3	4.8	2.0	6.8	.230	1.6	1.4	2.9	1.8
15	John Collins	PF	22	ATL	41	1363	23.5	.659	.243	.248	9.0	24.0	16.4	7.6	1.1	4.1	10.1	22.7	3.8	1.2	4.9	.174	3.7	-0.6	3.1	1.7
16	Montrezl Harrell	C	26	LAC	63	1749	23.2	.607	.022	.432	9.9	16.3	13.2	10.3	1.1	3.6	10.1	25.7	4.4	2.5	7.0	.191	2.5	0.5	2.9	2.2
17	Bradley Beal	SG	26	WAS	57	2053	23.2	.579	.369	.351	2.7	10.5	6.4	29.5	1.6	1.0	11.4	34.4	4.5	0.6	5.1	.118	5.3	-2.4	2.9	2.5
18	Christian Wood	PF	24	DET	62	1325	23.2	.659	.276	.476	8.8	24.8	16.7	7.6	1.3	3.4	12.0	23.0	3.6	1.5	5.1	.183	3.5	-0.3	3.1	1.7
19	Jonas Valančiūnas	C	27	MEM	70	1845	22.2	.631	.123	.271	12.4	32.2	22.5	10.9	0.8	3.6	13.3	21.5	4.2	2.8	7.0	.182	2.1	0.2	2.4	2.0
20	Andre Drummond	C	26	TOT	57	1879	22.0	.553	.045	.375	14.9	37.5	26.0	13.6	2.8	4.2	18.2	25.9	0.6	3.6	4.2	.108	-0.1	1.1	0.9	1.4

Fig 8: Top 20 PER of players in 2019-2020 NBA regular season

In the playoffs, due to the difference between the game system and the regular season, the top teams in the regular season of the East and the West will face each other in 4 out of 7 sets wins. This game method is somewhat similar to the game system of snooker and tennis. We follow the evaluation model of the game performance in the first question, and set the corresponding incentive coefficient p_0 and single game performance score P_i.

$$P_i = \frac{1}{2} + \frac{1}{1+e^{(-1)^{W_i}\frac{|\Delta_i|}{s}}}, (i = 1\ldots, 7) \tag{5.2}$$

in which, W_i is the game situation of the i-th round, $W_i = 1$ means victory, $W_i = 0$ means defeat, Δ_i means points difference, s takes a different value according to whether the game is a decisive game, if it is a tiebreaker, then s is taken a larger value used to control the difference in performance points (the ability to fight hard to the final game indicates that the two teams are close in strength). The team performance points for the entire series are:

$$P = p_0 \cdot \sum_i P_i \tag{5.3}$$

It is worth mentioning that due to the constant changes in the NBA game rhythm with the changes of the times, today's single game score difference is much larger than that of the game 10 or 20 years ago. Therefore, it needs to be based on the game rhythm of different eras. Adjust the value of s to obtain different expressions of single-field performance points P_i.

Therefore, the player's performance score P_i in this series is:

$$R_i = \frac{1}{1+e^{-k_i \cdot P \cdot w_i \cdot p_i}}, i = 1,2,3,4 \tag{5.4}$$

in which, k_i, P, w_i, p_i are series parameters, series team performance points, player series Wins value and series PER value respectively.

On the other hand, according to the intensity of each round of the regular season and the playoffs, similar to the previous model's game weight setting, different weights are given to the regular season, the first round of the playoffs, the division semifinals, the division finals, and the finals. $C_k (k = 0,1,2,3,4,$ and $C_0 > C_1 > C_2 > C_3 > C_4)$, and set the team promotion indicator function:

$$S(x) = \begin{cases} 1 & \text{The team advanced,} \\ 0 & \text{The team was eliminated.} \end{cases} \tag{5.5}$$

And the player injury indicator function:

$$\chi_i = \begin{cases} 1 & \text{The player missed more than half of the game because of injury,} \\ 0 & \text{others.} \end{cases} \tag{5.6}$$

The player's performance score in the season is divided into:

$$R_{game} = \sum_{i=0}^{4} C_i \left(1-\chi_i\right) R_i S(x) \tag{5.7}$$

For the various honors awarded by the NBA each season (regular season MVP, summary MVP, best team, All-Star, best rookie, DPOY, etc.) and the player's current season salary (salary level can be measured to a certain extent player ability and transaction value), after standard quantification based on historical data, the player's season honor points R_h and season salary points R_s are obtained. Thus, the player's performance score during this season is divided into:

$$R_{\text{season}} = \theta_1 R_{game} + \theta_2 R_h + \theta_3 R_S \tag{5.8}$$

$\theta_1, \theta_2, \theta_3$ respectively represent the weight of the three points in the season.

In the end, we can get the G.O.A.T performance score of a player who has been in the league for n years:

$$R_G = R_{pick} + \sum_{season=1}^{n} R_{season} \tag{5.9}$$

6. Letter

From: IMMC Team# 21897867

To: The Director of *Top Sport*

Date: March 20, 2021

Dear Director,

According to your requirements, we analyze results of 4 singles women's tennis Grand Slam tournaments in 2018 and form a Comprehensive Evaluation Model to measure athletes' "greatness" and find the best athlete in 2018. We also test our model with data of snooker players, figure out the G.O.A.T. from 2007 to 2017 and conclude some useful findings based on the analysis.

Before we start, we define the greatest athlete as the one who can achieve the greatest self-breakthrough and maintain a good performance at the same time. Therefore, we choose several factors contributing to this greatness: player's latest ranking, competition performance and ranking change before and after the tournament.

First, we take into account the athlete's expectation of winning and combine it with other factors indicating her performance in the competition to fairly update her ranking score after each tournament. As for the athlete's progress, we calculate the ratio of the ranking change to the former ranking to get the athlete's progress in every tournament. Then we combine the results from these two parts to get the conclusion that Simona Halep is the greatest female tennis player in 2018.

Owing to the comprehensive and flexible structure, our model has the following merits:

(1) The model makes full use of the information of rankings and competition results to precisely evaluate every athlete's performance.

(2) The update of athlete's ranking scores is thoughtfully and practically designed to meet the demand of fairness.

(3) When applying the model to other individual or team sports, you only need to change a few parameters to adopt to the new sport's rules.

To further prove the validity of our model, we test it with the example of snooker on a larger time scale. We collect data of 5 authoritative official competitions from 2007-2017 to figure out who is the greatest snooker player during this time.

First, we redefine the player's competition performance, making it cater to snooker's rules and modify the update formula of player's ranking score so that it will be able to realize the accumulation of his/her rankings over time. Besides, considering particular outstanding performance in snooker (breaking one hundred in a single stroke or getting whole 147 points), we give rewards to such accomplishments to further improve the model's precision and fairness.

After calculating overall evaluation scores of 103 snooker players from 2007 to 2017, we find that Mark Selby is the G.O.A.T in this period. On one thing, his ranking rose from 9th to 2nd and kept high for a relative long time; on the other, he reached the semi-finals of the 5 kind competitions we investigated for 25 times and entered the finals for 15 times (9 times championship, 60% winning rate). Observing players with high scores in our model, we find that those who achieves great progress unnecessarily rank among the top in the final results, while those who got higher ranking scores often achieved enough progress to make them at the top of our final G.O.A.T. list. This finding is exactly in line with our definition of "greatest" which verify the model's validity.

Thanks for taking the time out of your busy schedule to read our letter. Hope our advice can help.

IMMC Team # 21827183

7. References

[1] Lehmann R , Wohlrabe K . Who is the 'Journal Grand Master'? A new ranking based on the Elo rating system[J]. Journal of Informetrics, 2017, 11(3):800-809.
[2] Larsen, Richard J . An introduction to mathematical statistics and its applications[J]. Prentice-Hall, 2007.
[3] CUETRACKER. SNOOKER RESULTS & STATISTICS DATABASE. https://cuetracker.net/.
[4] NBA data sources
https://www.basketball-reference.com/
[5] Fig 8 source
https://www.basketball-reference.com/leagues/NBA_2020_advanced.html#advanced_stats::per

8. Attachment

Attachment 1: The ranking scores of woman tennis players of 2018

Name	Wimbledon Championships	French Open	US Open	Australian Open	Average Ranking Score
A Barty			1349		1349
A Kerber	1519	1464		1392	1458.3333
A Kontaveit		1292		1205	1248.5
A Sasnovich	990		1277		1133.5
A Sevastova			1432		1432
A Van Uytvanck	989				989
B Bencic	987				987
B Strycova		1261		1338	1299.5
C Garcia		1432		1420	1426
C Giorgi	1045				1045
C Suarez Navarro			1297	1040	1168.5
C Wozniacki		1457		1552	1504.5
D Allertova				1089	1089
D Cibulkova	1046		1250		1148
D Kasatkina	1412	1445			1428.5
D Vekic	989				989
E Makarova	977				977
E Mertens		1371	1375	1080	1275.3333
E Rodina	1087				1087
E Svitolina			1433	1489	1461
G Muguruza		1514			1514
J Gorges	1459				1459
J Ostapenko	1462				1462
K Bertens	1399				1399

K Kanepi			989		989
Ka Pliskova	1426		1479	1484	1463
L Tsurenko		989	1032		1010.5
M Buzamescu		1228			1228
M Keys		1460	1464	1421	1448.3333
M Rybarikova				1346	1346
M Sharapova		1271	1306		1288.5
M Vondrousova			980		980
N Osaka			1423	991	1207
P Martic				970	970
S Halep		1574		1546	1560
S Stephens		1518	1515		1516.5
S Williams	1443	1150	1439		1344
S-w Hsieh	978			988	983
Y Putintseva		1056			1056

Attachment 2: The progress of woman tennis players of 2018

Name	Wimbledon Championships	French Open	US Open	Australian Open	Average Progress
A Barty			-1.60%		-1.60%
A Kerber	6.52%	3.24%		3.49%	13.26%
A Kontaveit		-1.22%		-2.27%	-3.49%
A Sasnovich	-1.00%		-1.62%		-2.62%
A Sevastova			5.06%		5.06%
A Van Uytvanck	-1.10%				-1.10%
B Bencic	-1.30%				-1.30%
B Strycova		-2.85%		-1.18%	-4.03%
C Garcia		-1.51%		-1.87%	-3.38%
C Giorgi	4.50%				4.50%
C Suarez Navarro			3.26%	4.00%	7.26%
C Wozniacki		-1.95%		4.44%	2.49%
D Allertova				-1.00%	-1.00%
D Cibulkova	4.60%		-1.34%		3.26%
D Kasatkina	0.64%	2.99%			3.64%
D Vekic	-1.10%				-1.10%
E Makarova	-2.30%				-2.30%
E Mertens		-1.22%	-1.43%	8.00%	5.34%
E Rodina	-1.18%				-1.18%
E Svitolina			-1.44%	1.02%	-0.43%
G Muguruza		2.30%			2.30%
J Gorges	3.40%				3.40%
J Ostapenko	3.10%				3.10%
K Bertens	3.32%				3.32%
K Kanepi			-1.10%		-1.10%
Ka Pliskova	-1.93%		2.21%	1.64%	1.93%
L Tsurenko		-1.10%	3.20%		2.10%

M Buzamescu		-1.37%			-1.37%
M Keys		3.47%	4.35%	3.05%	10.87%
M Rybarikova				-1.25%	-1.25%
M Sharapova		-0.55%	-2.25%		-2.79%
M Vondrousova			-2.00%		-2.00%
N Osaka			5.10%	-0.90%	4.20%
P Martic				-3.00%	-3.00%
S Halep		5.50%		3.62%	9.12%
S Stephens		5.93%	2.36%		8.30%
S Williams	5.71%	0.00%	4.35%		10.07%
S-w Hsieh	-2.20%			-1.20%	-3.40%
Y Putintseva		5.60%			5.60%

Attachment 3: The comprehensive scores of woman tennis players of 2018

Name	RSM	PM	CEM
A Barty	15	30	24
A Kerber	9	1	4.2
A Kontaveit	21	38	31.2
A Sasnovich	26	33	30.2
A Sevastova	11	9	9.8
A Van Uytvanck	32	23	26.6
B Bencic	35	28	30.8
B Strycova	17	39	30.2
C Garcia	13	36	26.8
C Giorgi	30	10	18
C Suarez Navarro	24	6	13.2
C Wozniacki	4	17	11.8
D Allertova	27	22	24
D Cibulkova	25	15	19
D Kasatkina	12	12	12
D Vekic	33	24	27.6
E Makarova	38	32	34.4
E Mertens	19	8	12.4
E Rodina	28	26	26.8
E Svitolina	7	21	15.4
G Muguruza	3	18	12
J Gorges	8	13	11
J Ostapenko	6	16	12
K Bertens	14	14	14
K Kanepi	34	25	28.6
Ka Pliskova	5	20	14
L Tsurenko	31	19	23.8
M Buzamescu	22	29	26.2
M Keys	10	2	5.2
M Rybarikova	16	27	22.6
M Sharapova	18	34	27.6

M Vondrousova	37	31	33.4
N Osaka	23	11	15.8
P Martic	39	35	36.6
S Halep	1	4	2.8
S Stephens	2	5	3.8
S Williams	20	3	9.8
S-w Hsieh	36	37	36.6
Y Putintseva	29	7	15.8

Attachment 4: Snooker competition data

Data for 2007

Name	round	year	match	win	H	C
Ronnie O'Sullivan	**5**	2007	CO	1	16	4
Ali Carter	4	2007	CO	0	16	4
Shaun Murphy	**5**	2007	CO	1	16	4
Stephen Maguire	2	2007	CO	0	16	4
John Higgins	**5**	2007	CO	1	16	4
Jimmy White	1	2007	CO	0	16	4
Barry Hawkins	**5**	2007	CO	1	16	4
Joe Swail	0	2007	CO	0	16	4
Marco Fu	**5**	2007	CO	1	16	4
Matthew Stevens	3	2007	CO	0	16	4
Graeme Dott	**5**	2007	CO	1	16	4
Neil Robertson	1	2007	CO	0	16	4
Ken Doherty	**5**	2007	CO	1	16	4
Mark Selby	1	2007	CO	0	16	4
Jamie Cope	**5**	2007	CO	1	16	4
Stuart Bingham	4	2007	CO	0	16	4
Ronnie O'Sullivan	**5**	2007	CO	1	16	2
Marco Fu	3	2007	CO	0	16	2
Barry Hawkins	**5**	2007	CO	1	16	2
Ken Doherty	4	2007	CO	0	16	2
Graeme Dott	**5**	2007	CO	1	16	2
John Higgins	2	2007	CO	0	16	2
Jamie Cope	**5**	2007	CO	1	16	2
Shaun Murphy	0	2007	CO	0	16	2
Graeme Dott	**6**	2007	CO	1	16	1
Ronnie O'Sullivan	2	2007	CO	0	16	1
Jamie Cope	**6**	2007	CO	1	16	1
Barry Hawkins	5	2007	CO	0	16	1
Graeme Dott	**9**	2007	CO	1	16	0.5
Jamie Cope	5	2007	CO	0	16	0.5
Matthew Stevens	**5**	2007	SM	1	8	4
Stephen Maguire	4	2007	SM	0	8	4
Mark Selby	**5**	2007	SM	1	8	4

John Higgins	3	2007	SM	0	8	4
Stephen Lee	**5**	2007	SM	1	8	4
Stephen Hendry	3	2007	SM	0	8	4
Dave Harold	**5**	2007	SM	1	8	4
Steve Davis	1	2007	SM	0	8	4
Graeme Dott	**5**	2007	SM	1	8	4
Ding Junhui	1	2007	SM	0	8	4
Ryan Day	**5**	2007	SM	1	8	4
Ian McCulloch	3	2007	SM	0	8	4
Dominic Dale	**5**	2007	SM	1	8	4
Adrian Gunnell	1	2007	SM	0	8	4
Stuart Bingham	**5**	2007	SM	1	8	4
Stuart Pettman	4	2007	SM	0	8	4
Mark Selby	**5**	2007	SM	1	8	2
Stuart Bingham	0	2007	SM	0	8	2
Graeme Dott	**5**	2007	SM	1	8	2
Stephen Lee	4	2007	SM	0	8	2
Ryan Day	**5**	2007	SM	1	8	2
Matthew Stevens	4	2007	SM	0	8	2
Dominic Dale	**5**	2007	SM	1	8	2
Dave Harold	1	2007	SM	0	8	2
Ryan Day	**6**	2007	SM	1	8	1
Graeme Dott	2	2007	SM	0	8	1
Dominic Dale	**6**	2007	SM	1	8	1
Mark Selby	3	2007	SM	0	8	1
Dominic Dale	**10**	2007	SM	1	8	0.5
Ryan Day	6	2007	SM	0	8	0.5
Mark Williams	**9**	2007	UK	1	8	4
Mark Allen	5	2007	UK	0	8	4
Mark Selby	**9**	2007	UK	1	8	4
Dave Harold	2	2007	UK	0	8	4
Ronnie O'Sullivan	**9**	2007	UK	1	8	4
Mark King	1	2007	UK	0	8	4
Shaun Murphy	**9**	2007	UK	1	8	4
Stuart Bingham	3	2007	UK	0	8	4
Stephen Maguire	**9**	2007	UK	1	8	4
Ian McCulloch	5	2007	UK	0	8	4
Ding Junhui	**9**	2007	UK	1	8	4
Nigel Bond	5	2007	UK	0	8	4
Marco Fu	**9**	2007	UK	1	8	4
Joe Perry	2	2007	UK	0	8	4
Jamie Cope	**9**	2007	UK	1	8	4
Barry Hawkins	8	2007	UK	0	8	4
Mark Selby	**9**	2007	UK	1	8	2
Marco Fu	7	2007	UK	0	8	2
Ronnie O'Sullivan	**9**	2007	UK	1	8	2
Jamie Cope	2	2007	UK	0	8	2
Shaun Murphy	**9**	2007	UK	1	8	2

Ding Junhui	7	2007	UK	0	8	2
Stephen Maguire	**9**	2007	UK	1	8	2
Mark Williams	5	2007	UK	0	8	2
Ronnie O'Sullivan	**9**	2007	UK	1	8	1
Mark Selby	8	2007	UK	0	8	1
Stephen Maguire	**9**	2007	UK	1	8	1
Shaun Murphy	5	2007	UK	0	8	1
Ronnie O'Sullivan	**10**	2007	UK	1	8	0.5
Stephen Maguire	2	2007	UK	0	8	0.5
Neil Robertson	**5**	2007	WO	1	16	4
Stephen Hendry	3	2007	WO	0	16	4
Ronnie O'Sullivan	**5**	2007	WO	1	16	4
Mark Selby	1	2007	WO	0	16	4
Shaun Murphy	**5**	2007	WO	1	16	4
Jamie Burnett	4	2007	WO	0	16	4
Stephen Maguire	**5**	2007	WO	1	16	4
Ken Doherty	3	2007	WO	0	16	4
Andrew Higginson	**5**	2007	WO	1	16	4
Michael Judge	1	2007	WO	0	16	4
Anthony Hamilton	**5**	2007	WO	1	16	4
Dave Harold	3	2007	WO	0	16	4
Steve Davis	**5**	2007	WO	1	16	4
Graeme Dott	3	2007	WO	0	16	4
Ali Carter	**5**	2007	WO	1	16	4
Nigel Bond	4	2007	WO	0	16	4
Neil Robertson	**5**	2007	WO	1	16	2
Ronnie O'Sullivan	4	2007	WO	0	16	2
Stephen Maguire	**5**	2007	WO	1	16	2
Shaun Murphy	3	2007	WO	0	16	2
Andrew Higginson	**5**	2007	WO	1	16	2
Ali Carter	1	2007	WO	0	16	2
Steve Davis	**5**	2007	WO	1	16	2
Anthony Hamilton	4	2007	WO	0	16	2
Neil Robertson	**6**	2007	WO	1	16	1
Steve Davis	3	2007	WO	0	16	1
Andrew Higginson	**6**	2007	WO	1	16	1
Stephen Maguire	3	2007	WO	0	16	1
Neil Robertson	**9**	2007	WO	1	16	0.5
Andrew Higginson	8	2007	WO	0	16	0.5
Matthew Stevens	**13**	2007	WC	1	8	4
Mark Allen	9	2007	WC	0	8	4
Mark Selby	**13**	2007	WC	1	8	4
Peter Ebdon	8	2007	WC	0	8	4
Ronnie O'Sullivan	**13**	2007	WC	1	8	4
Neil Robertson	10	2007	WC	0	8	4
Shaun Murphy	**13**	2007	WC	1	8	4
John Parrott	8	2007	WC	0	8	4
Stephen Maguire	**13**	2007	WC	1	8	4

Joe Swail	8	2007	WC	0	8	4
John Higgins	**13**	2007	WC	1	8	4
Fergal O'Brien	4	2007	WC	0	8	4
Anthony Hamilton	**13**	2007	WC	1	8	4
Ian McCulloch	8	2007	WC	0	8	4
Ali Carter	**13**	2007	WC	1	8	4
Stephen Hendry	6	2007	WC	0	8	4
Mark Selby	**13**	2007	WC	1	8	2
Ali Carter	12	2007	WC	0	8	2
Shaun Murphy	**13**	2007	WC	1	8	2
Matthew Stevens	12	2007	WC	0	8	2
Stephen Maguire	**13**	2007	WC	1	8	2
Anthony Hamilton	7	2007	WC	0	8	2
John Higgins	**13**	2007	WC	1	8	2
Ronnie O'Sullivan	9	2007	WC	0	8	2
Mark Selby	**17**	2007	WC	1	8	1
Shaun Murphy	16	2007	WC	0	8	1
John Higgins	**17**	2007	WC	1	8	1
Stephen Maguire	15	2007	WC	0	8	1
John Higgins	**18**	2007	WC	1	8	0.5
Mark Selby	13	2007	WC	0	8	0.5

Data for 2008

Name	round	year	match	win	H	C
Mark Williams	**5**	2008	CO	1	16	4
Peter Ebdon	2	2008	CO	0	16	4
Mark Selby	**5**	2008	CO	1	16	4
Marco Fu	3	2008	CO	0	16	4
Shaun Murphy	**5**	2008	CO	1	16	4
Ding Junhui	4	2008	CO	0	16	4
Stephen Maguire	**5**	2008	CO	1	16	4
Barry Hawkins	2	2008	CO	0	16	4
John Higgins	**5**	2008	CO	1	16	4
Mark King	1	2008	CO	0	16	4
Ryan Day	**5**	2008	CO	1	16	4
Ken Doherty	3	2008	CO	0	16	4
Nigel Bond	**5**	2008	CO	1	16	4
Barry Pinches	1	2008	CO	0	16	4
Mark Allen	**5**	2008	CO	1	16	4
Ali Carter	3	2008	CO	0	16	4
Mark Selby	**5**	2008	CO	1	16	2
John Higgins	2	2008	CO	0	16	2
Shaun Murphy	**5**	2008	CO	1	16	2
Mark Allen	3	2008	CO	0	16	2
Stephen Maguire	**5**	2008	CO	1	16	2
Nigel Bond	0	2008	CO	0	16	2

Ryan Day	**5**	2008	CO	1	16	2
Mark Williams	3	2008	CO	0	16	2
Shaun Murphy	**6**	2008	CO	1	16	1
Mark Selby	3	2008	CO	0	16	1
Stephen Maguire	**6**	2008	CO	1	16	1
Ryan Day	5	2008	CO	0	16	1
Stephen Maguire	**10**	2008	CO	1	16	0.5
Shaun Murphy	9	2008	CO	0	16	0.5
Mark Williams	**5**	2008	SM	1	8	4
Jamie Cope	2	2008	SM	0	8	4
Ricky Walden	**5**	2008	SM	1	8	4
Neil Robertson	4	2008	SM	0	8	4
Mark Selby	**5**	2008	SM	1	8	4
Mark King	0	2008	SM	0	8	4
Ronnie O'Sullivan	**5**	2008	SM	1	8	4
Joe Perry	3	2008	SM	0	8	4
Stephen Maguire	**5**	2008	SM	1	8	4
Stuart Bingham	3	2008	SM	0	8	4
Marco Fu	**5**	2008	SM	1	8	4
Andy Hicks	2	2008	SM	0	8	4
Ryan Day	**5**	2008	SM	1	8	4
John Higgins	3	2008	SM	0	8	4
Steve Davis	**5**	2008	SM	1	8	4
Dave Harold	4	2008	SM	0	8	4
Ricky Walden	**5**	2008	SM	1	8	2
Steve Davis	2	2008	SM	0	8	2
Mark Selby	**5**	2008	SM	1	8	2
Marco Fu	3	2008	SM	0	8	2
Ronnie O'Sullivan	**5**	2008	SM	1	8	2
Mark Williams	3	2008	SM	0	8	2
Stephen Maguire	**5**	2008	SM	1	8	2
Ryan Day	4	2008	SM	0	8	2
Ricky Walden	**6**	2008	SM	1	8	1
Mark Selby	4	2008	SM	0	8	1
Ronnie O'Sullivan	**6**	2008	SM	1	8	1
Stephen Maguire	5	2008	SM	0	8	1
Ricky Walden	**10**	2008	SM	1	8	0.5
Ronnie O'Sullivan	8	2008	SM	0	8	0.5
Mark Williams	**9**	2008	UK	1	8	4
Graeme Dott	7	2008	UK	0	8	4
Joe Perry	**9**	2008	UK	1	8	4
Ronnie O'Sullivan	5	2008	UK	0	8	4
Shaun Murphy	**9**	2008	UK	1	8	4
Mark Allen	7	2008	UK	0	8	4
Stephen Maguire	**9**	2008	UK	1	8	4
Neil Robertson	8	2008	UK	0	8	4
Ali Carter	**9**	2008	UK	1	8	4
Peter Ebdon	5	2008	UK	0	8	4

Stephen Lee	**9**	2008	UK	1	8	4
Mark King	5	2008	UK	0	8	4
John Higgins	**9**	2008	UK	1	8	4
Ding Junhui	4	2008	UK	0	8	4
Marco Fu	**9**	2008	UK	1	8	4
Matthew Stevens	5	2008	UK	0	8	4
Shaun Murphy	**9**	2008	UK	1	8	2
Stephen Lee	7	2008	UK	0	8	2
Stephen Maguire	**9**	2008	UK	1	8	2
John Higgins	7	2008	UK	0	8	2
Marco Fu	**9**	2008	UK	1	8	2
Joe Perry	7	2008	UK	0	8	2
Ali Carter	**9**	2008	UK	1	8	2
Mark Williams	8	2008	UK	0	8	2
Shaun Murphy	**9**	2008	UK	1	8	1
Stephen Maguire	4	2008	UK	0	8	1
Marco Fu	**9**	2008	UK	1	8	1
Ali Carter	7	2008	UK	0	8	1
Shaun Murphy	**10**	2008	UK	1	8	0.5
Marco Fu	9	2008	UK	0	8	0.5
Mark Selby	**5**	2008	WO	1	16	4
Ken Doherty	2	2008	WO	0	16	4
Joe Perry	**5**	2008	WO	1	16	4
Stuart Bingham	2	2008	WO	0	16	4
Ronnie O'Sullivan	**5**	2008	WO	1	16	4
Steve Davis	3	2008	WO	0	16	4
Shaun Murphy	**5**	2008	WO	1	16	4
Mark Williams	2	2008	WO	0	16	4
Stephen Lee	**5**	2008	WO	1	16	4
Michael Judge	2	2008	WO	0	16	4
John Higgins	**5**	2008	WO	1	16	4
Ding Junhui	1	2008	WO	0	16	4
Stephen Hendry	**5**	2008	WO	1	16	4
Ryan Day	4	2008	WO	0	16	4
Ali Carter	**5**	2008	WO	1	16	4
Neil Robertson	3	2008	WO	0	16	4
Mark Selby	**5**	2008	WO	1	16	2
John Higgins	2	2008	WO	0	16	2
Ronnie O'Sullivan	**5**	2008	WO	1	16	2
Ali Carter	4	2008	WO	0	16	2
Shaun Murphy	**5**	2008	WO	1	16	2
Joe Perry	0	2008	WO	0	16	2
Stephen Hendry	**5**	2008	WO	1	16	2
Stephen Lee	2	2008	WO	0	16	2
Mark Selby	**6**	2008	WO	1	16	1
Stephen Hendry	4	2008	WO	0	16	1
Ronnie O'Sullivan	**6**	2008	WO	1	16	1
Shaun Murphy	3	2008	WO	0	16	1

Mark Selby	**9**	2008	WO	1	16	0.5
Ronnie O'Sullivan	8	2008	WO	0	16	0.5
Liang Wenbo	**13**	2008	WC	1	8	4
Joe Swail	12	2008	WC	0	8	4
Joe Perry	**13**	2008	WC	1	8	4
Stuart Bingham	9	2008	WC	0	8	4
Ronnie O'Sullivan	**13**	2008	WC	1	8	4
Mark Williams	7	2008	WC	0	8	4
Stephen Maguire	**13**	2008	WC	1	8	4
Neil Robertson	7	2008	WC	0	8	4
Stephen Hendry	**13**	2008	WC	1	8	4
Ding Junhui	7	2008	WC	0	8	4
Peter Ebdon	**13**	2008	WC	1	8	4
Mark King	9	2008	WC	0	8	4
Ryan Day	**13**	2008	WC	1	8	4
John Higgins	9	2008	WC	0	8	4
Ali Carter	**13**	2008	WC	1	8	4
Shaun Murphy	4	2008	WC	0	8	4
Joe Perry	**13**	2008	WC	1	8	2
Stephen Maguire	12	2008	WC	0	8	2
Ronnie O'Sullivan	**13**	2008	WC	1	8	2
Liang Wenbo	7	2008	WC	0	8	2
Stephen Hendry	**13**	2008	WC	1	8	2
Ryan Day	7	2008	WC	0	8	2
Ali Carter	**13**	2008	WC	1	8	2
Peter Ebdon	9	2008	WC	0	8	2
Ronnie O'Sullivan	**17**	2008	WC	1	8	1
Stephen Hendry	6	2008	WC	0	8	1
Ali Carter	**17**	2008	WC	1	8	1
Joe Perry	15	2008	WC	0	8	1
Ronnie O'Sullivan	**18**	2008	WC	1	8	0.5
Ali Carter	8	2008	WC	0	8	0.5

Data for 2009

Name	round	year	match	win	H	C
Stuart Pettman	**5**	2009	CO	1	16	4
Ali Carter	2	2009	CO	0	16	4
Ronnie O'Sullivan	**5**	2009	CO	1	16	4
Xiao Guodong	3	2009	CO	0	16	4
Shaun Murphy	**5**	2009	CO	1	16	4
Neil Robertson	1	2009	CO	0	16	4
John Higgins	**5**	2009	CO	1	16	4
Tian Pengfei	2	2009	CO	0	16	4
Stephen Hendry	**5**	2009	CO	1	16	4
Ricky Walden	4	2009	CO	0	16	4

Peter Ebdon	**5**	2009	CO	1	16	4
Dave Harold	3	2009	CO	0	16	4
Graeme Dott	**5**	2009	CO	1	16	4
Mark Selby	1	2009	CO	0	16	4
Ryan Day	**5**	2009	CO	1	16	4
Mark King	2	2009	CO	0	16	4
Stuart Pettman	**5**	2009	CO	1	16	2
Graeme Dott	2	2009	CO	0	16	2
John Higgins	**5**	2009	CO	1	16	2
Ronnie O'Sullivan	4	2009	CO	0	16	2
Peter Ebdon	**5**	2009	CO	1	16	2
Stephen Hendry	1	2009	CO	0	16	2
Ryan Day	**5**	2009	CO	1	16	2
Shaun Murphy	0	2009	CO	0	16	2
John Higgins	**6**	2009	CO	1	16	1
Ryan Day	4	2009	CO	0	16	1
Peter Ebdon	**6**	2009	CO	1	16	1
Stuart Pettman	1	2009	CO	0	16	1
Peter Ebdon	**10**	2009	CO	1	16	0.5
John Higgins	8	2009	CO	0	16	0.5
Liang Wenbo	**5**	2009	SM	1	8	4
Ali Carter	0	2009	SM	0	8	4
Ricky Walden	**5**	2009	SM	1	8	4
Stephen Hendry	1	2009	SM	0	8	4
Ronnie O'Sullivan	**5**	2009	SM	1	8	4
Marco Fu	2	2009	SM	0	8	4
Shaun Murphy	**5**	2009	SM	1	8	4
Jamie Cope	0	2009	SM	0	8	4
Ding Junhui	**5**	2009	SM	1	8	4
Stuart Bingham	2	2009	SM	0	8	4
John Higgins	**5**	2009	SM	1	8	4
Mark Williams	1	2009	SM	0	8	4
Ken Doherty	**5**	2009	SM	1	8	4
Barry Hawkins	4	2009	SM	0	8	4
Ryan Day	**5**	2009	SM	1	8	4
Matthew Stevens	4	2009	SM	0	8	4
Ricky Walden	**5**	2009	SM	1	8	2
Steve Davis	2	2009	SM	0	8	2
Mark Selby	**5**	2009	SM	1	8	2
Marco Fu	3	2009	SM	0	8	2
Ronnie O'Sullivan	**5**	2009	SM	1	8	2
Mark Williams	3	2009	SM	0	8	2
Stephen Maguire	**5**	2009	SM	1	8	2
Ryan Day	4	2009	SM	0	8	2
Ricky Walden	**6**	2009	SM	1	8	1
Mark Selby	4	2009	SM	0	8	1
Ronnie O'Sullivan	**6**	2009	SM	1	8	1
Stephen Maguire	5	2009	SM	0	8	1

Ricky Walden	**10**	2009	SM	1	8	0.5
Ronnie O'Sullivan	8	2009	SM	0	8	0.5
Ding Junhui	**9**	2009	UK	1	8	4
Shaun Murphy	3	2009	UK	0	8	4
Ali Carter	**9**	2009	UK	1	8	4
Stephen Lee	5	2009	UK	0	8	4
Stephen Maguire	**9**	2009	UK	1	8	4
Stuart Bingham	3	2009	UK	0	8	4
Peter Lines	**9**	2009	UK	1	8	4
Mark Williams	8	2009	UK	0	8	4
John Higgins	**9**	2009	UK	1	8	4
Neil Robertson	8	2009	UK	0	8	4
Liang Wenbo	**9**	2009	UK	1	8	4
Mark King	2	2009	UK	0	8	4
Ronnie O'Sullivan	**9**	2009	UK	1	8	4
Peter Ebdon	3	2009	UK	0	8	4
Mark Selby	**9**	2009	UK	1	8	4
Stephen Hendry	5	2009	UK	0	8	4
Ding Junhui	**9**	2009	UK	1	8	2
Ali Carter	8	2009	UK	0	8	2
Stephen Maguire	**9**	2009	UK	1	8	2
Peter Lines	5	2009	UK	0	8	2
John Higgins	**9**	2009	UK	1	8	2
Liang Wenbo	2	2009	UK	0	8	2
Ronnie O'Sullivan	**9**	2009	UK	1	8	2
Mark Selby	3	2009	UK	0	8	2
Ding Junhui	**9**	2009	UK	1	8	1
Stephen Maguire	5	2009	UK	0	8	1
John Higgins	**9**	2009	UK	1	8	1
Ronnie O'Sullivan	8	2009	UK	0	8	1
Ding Junhui	**10**	2009	UK	1	8	0.5
John Higgins	8	2009	UK	0	8	0.5
Ali Carter	**5**	2009	WO	1	16	4
Graeme Dott	4	2009	WO	0	16	4
Shaun Murphy	**5**	2009	WO	1	16	4
Mark King	2	2009	WO	0	16	4
Anthony Hamilton	**5**	2009	WO	1	16	4
Michael Judge	2	2009	WO	0	16	4
Mark Selby	**5**	2009	WO	1	16	4
David Gilbert	1	2009	WO	0	16	4
Joe Swail	**5**	2009	WO	1	16	4
Martin Gould	1	2009	WO	0	16	4
Stephen Maguire	**5**	2009	WO	1	16	4
Ding Junhui	4	2009	WO	0	16	4
Neil Robertson	**5**	2009	WO	1	16	4
John Higgins	4	2009	WO	0	16	4
Marco Fu	**5**	2009	WO	1	16	4
Ronnie O'Sullivan	3	2009	WO	0	16	4

Ali Carter	**5**	2009	WO	1	16	2
Shaun Murphy	3	2009	WO	0	16	2
Anthony Hamilton	**5**	2009	WO	1	16	2
Mark Selby	3	2009	WO	0	16	2
Joe Swail	**5**	2009	WO	1	16	2
Stephen Maguire	4	2009	WO	0	16	2
Neil Robertson	**5**	2009	WO	1	16	2
Marco Fu	2	2009	WO	0	16	2
Ali Carter	**6**	2009	WO	1	16	1
Anthony Hamilton	5	2009	WO	0	16	1
Joe Swail	**6**	2009	WO	1	16	1
Neil Robertson	4	2009	WO	0	16	1
Ali Carter	**9**	2009	WO	1	16	0.5
Joe Swail	5	2009	WO	0	16	0.5
John Higgins	**13**	2009	WC	1	8	4
Jamie Cope	12	2009	WC	0	8	4
Mark Selby	**13**	2009	WC	1	8	4
Graeme Dott	10	2009	WC	0	8	4
Mark Allen	**13**	2009	WC	1	8	4
Ronnie O'Sullivan	11	2009	WC	0	8	4
Ryan Day	**13**	2009	WC	1	8	4
Nigel Bond	5	2009	WC	0	8	4
Shaun Murphy	**13**	2009	WC	1	8	4
Marco Fu	3	2009	WC	0	8	4
Stephen Hendry	**13**	2009	WC	1	8	4
Ding Junhui	10	2009	WC	0	8	4
Neil Robertson	**13**	2009	WC	1	8	4
Ali Carter	8	2009	WC	0	8	4
Stephen Maguire	**13**	2009	WC	1	8	4
Mark King	6	2009	WC	0	8	4
John Higgins	**13**	2009	WC	1	8	2
Mark Selby	12	2009	WC	0	8	2
Mark Allen	**13**	2009	WC	1	8	2
Ryan Day	11	2009	WC	0	8	2
Shaun Murphy	**13**	2009	WC	1	8	2
Stephen Hendry	11	2009	WC	0	8	2
Neil Robertson	**13**	2009	WC	1	8	2
Stephen Maguire	8	2009	WC	0	8	2
John Higgins	**17**	2009	WC	1	8	1
Mark Allen	13	2009	WC	0	8	1
Shaun Murphy	**17**	2009	WC	1	8	1
Neil Robertson	14	2009	WC	0	8	1
John Higgins	**18**	2009	WC	1	8	0.5
Shaun Murphy	9	2009	WC	0	8	0.5

Data for 2010

Name	round	year	match	win	H	C
Mark Williams	**5**	2010	CO	1	16	4
John Higgins	2	2010	CO	0	16	4
Marco Fu	**5**	2010	CO	1	16	4
Nigel Bond	3	2010	CO	0	16	4
Ali Carter	**5**	2010	CO	1	16	4
Joe Perry	3	2010	CO	0	16	4
Mark King	**5**	2010	CO	1	16	4
Tian Pengfei	3	2010	CO	0	16	4
Ding Junhui	**5**	2010	CO	1	16	4
Mark Selby	3	2010	CO	0	16	4
Peter Ebdon	**5**	2010	CO	1	16	4
Neil Robertson	1	2010	CO	0	16	4
Mark Allen	**5**	2010	CO	1	16	4
Stephen Maguire	3	2010	CO	0	16	4
Stephen Hendry	**5**	2010	CO	1	16	4
Ryan Day	0	2010	CO	0	16	4
Mark Williams	**5**	2010	CO	1	16	2
Marco Fu	1	2010	CO	0	16	2
Ali Carter	**5**	2010	CO	1	16	2
Mark King	1	2010	CO	0	16	2
Ding Junhui	**5**	2010	CO	1	16	2
Peter Ebdon	2	2010	CO	0	16	2
Mark Allen	**5**	2010	CO	1	16	2
Stephen Hendry	4	2010	CO	0	16	2
Mark Williams	**6**	2010	CO	1	16	1
Ali Carter	4	2010	CO	0	16	1
Ding Junhui	**6**	2010	CO	1	16	1
Mark Allen	2	2010	CO	0	16	1
Mark Williams	**10**	2010	CO	1	16	0.5
Ding Junhui	6	2010	CO	0	16	0.5
Ali Carter	**5**	2010	SM	1	8	4
Stuart Bingham	3	2010	SM	0	8	4
Matthew Stevens	**5**	2010	SM	1	8	4
Shaun Murphy	2	2010	SM	0	8	4
Mark Selby	**5**	2010	SM	1	8	4
Martin Gould	4	2010	SM	0	8	4
Mark King	**5**	2010	SM	1	8	4
Peter Ebdon	3	2010	SM	0	8	4
Jamie Burnett	**5**	2010	SM	1	8	4
Andrew Higginson	0	2010	SM	0	8	4
Mark Davis	**5**	2010	SM	1	8	4
Stephen Maguire	3	2010	SM	0	8	4
Jamie Cope	**5**	2010	SM	1	8	4
Ding Junhui	1	2010	SM	0	8	4
Graeme Dott	**5**	2010	SM	1	8	4
Mark Williams	4	2010	SM	0	8	4

Ali Carter	**5**	2010	SM	1	8	2
Matthew Stevens	4	2010	SM	0	8	2
Mark Selby	**5**	2010	SM	1	8	2
Mark King	1	2010	SM	0	8	2
Jamie Burnett	**5**	2010	SM	1	8	2
Mark Davis	4	2010	SM	0	8	2
Jamie Cope	**5**	2010	SM	1	8	2
Graeme Dott	2	2010	SM	0	8	2
Ali Carter	**6**	2010	SM	1	8	1
Mark Selby	2	2010	SM	0	8	1
Jamie Burnett	**6**	2010	SM	1	8	1
Jamie Cope	1	2010	SM	0	8	1
Ali Carter	**10**	2010	SM	1	8	0.5
Jamie Burnett	7	2010	SM	0	8	0.5
John Higgins	**9**	2010	UK	1	8	4
Graeme Dott	8	2010	UK	0	8	4
Stephen Maguire	**9**	2010	UK	1	8	4
Mark Selby	7	2010	UK	0	8	4
Mark Allen	**9**	2010	UK	1	8	4
Ding Junhui	8	2010	UK	0	8	4
Stuart Bingham	**9**	2010	UK	1	8	4
Marco Fu	2	2010	UK	0	8	4
Mark Williams	**9**	2010	UK	1	8	4
Stephen Hendry	6	2010	UK	0	8	4
Mark Joyce	**9**	2010	UK	1	8	4
Judd Trump	7	2010	UK	0	8	4
Shaun Murphy	**9**	2010	UK	1	8	4
Ryan Day	8	2010	UK	0	8	4
Neil Robertson	**9**	2010	UK	1	8	4
Andrew Higginson	5	2010	UK	0	8	4
John Higgins	**9**	2010	UK	1	8	2
Stephen Maguire	7	2010	UK	0	8	2
Mark Allen	**9**	2010	UK	1	8	2
Stuart Bingham	7	2010	UK	0	8	2
Mark Williams	**9**	2010	UK	1	8	2
Mark Joyce	7	2010	UK	0	8	2
Shaun Murphy	**9**	2010	UK	1	8	2
Neil Robertson	7	2010	UK	0	8	2
John Higgins	**9**	2010	UK	1	8	1
Mark Allen	5	2010	UK	0	8	1
Mark Williams	**9**	2010	UK	1	8	1
Shaun Murphy	8	2010	UK	0	8	1
John Higgins	**10**	2010	UK	1	8	0.5
Mark Williams	9	2010	UK	0	8	0.5
John Higgins	**5**	2010	WO	1	16	4
Graeme Dott	1	2010	WO	0	16	4
Mark Selby	**5**	2010	WO	1	16	4
Mark King	3	2010	WO	0	16	4

Ronnie O'Sullivan	**5**	2010	WO	1	16	4
Jamie Cope	0	2010	WO	0	16	4
Mark Allen	**5**	2010	WO	1	16	4
Matthew Stevens	2	2010	WO	0	16	4
Ali Carter	**5**	2010	WO	1	16	4
Neil Robertson	2	2010	WO	0	16	4
Ryan Day	**5**	2010	WO	1	16	4
Stephen Hendry	3	2010	WO	0	16	4
Stephen Maguire	**5**	2010	WO	1	16	4
Barry Hawkins	1	2010	WO	0	16	4
Mark Williams	**5**	2010	WO	1	16	4
Andrew Higginson	0	2010	WO	0	16	4
John Higgins	**5**	2010	WO	1	16	2
Mark Selby	2	2010	WO	0	16	2
Ronnie O'Sullivan	**5**	2010	WO	1	16	2
Mark Allen	2	2010	WO	0	16	2
Ali Carter	**5**	2010	WO	1	16	2
Ryan Day	2	2010	WO	0	16	2
Stephen Maguire	**5**	2010	WO	1	16	2
Mark Williams	1	2010	WO	0	16	2
John Higgins	**6**	2010	WO	1	16	1
Ronnie O'Sullivan	4	2010	WO	0	16	1
Ali Carter	**6**	2010	WO	1	16	1
Stephen Maguire	3	2010	WO	0	16	1
John Higgins	**9**	2010	WO	1	16	0.5
Ali Carter	4	2010	WO	0	16	0.5
Neil Robertson	**13**	2010	WC	1	8	4
Martin Gould	12	2010	WC	0	8	4
Steve Davis	**13**	2010	WC	1	8	4
John Higgins	11	2010	WC	0	8	4
Ali Carter	**13**	2010	WC	1	8	4
Joe Perry	11	2010	WC	0	8	4
Shaun Murphy	**13**	2010	WC	1	8	4
Ding Junhui	10	2010	WC	0	8	4
Graeme Dott	**13**	2010	WC	1	8	4
Stephen Maguire	6	2010	WC	0	8	4
Mark Allen	**13**	2010	WC	1	8	4
Mark Davis	5	2010	WC	0	8	4
Mark Selby	**13**	2010	WC	1	8	4
Stephen Hendry	5	2010	WC	0	8	4
Ronnie O'Sullivan	**13**	2010	WC	1	8	4
Mark Williams	10	2010	WC	0	8	4
Neil Robertson	**13**	2010	WC	1	8	2
Steve Davis	5	2010	WC	0	8	2
Ali Carter	**13**	2010	WC	1	8	2
Shaun Murphy	12	2010	WC	0	8	2
Graeme Dott	**13**	2010	WC	1	8	2
Mark Allen	12	2010	WC	0	8	2

Mark Selby	**13**	2010	WC	1	8	2
Ronnie O'Sullivan	11	2010	WC	0	8	2
Neil Robertson	**17**	2010	WC	1	8	1
Ali Carter	12	2010	WC	0	8	1
Graeme Dott	**17**	2010	WC	1	8	1
Mark Selby	14	2010	WC	0	8	1
Neil Robertson	**18**	2010	WC	1	8	0.5
Graeme Dott	13	2010	WC	0	8	0.5

Data for 2011

Name	round	year	match	win	H	C
Judd Trump	**5**	2011	CO	1	16	4
Mark Davis	2	2011	CO	0	16	4
Peter Ebdon	**5**	2011	CO	1	16	4
Neil Robertson	1	2011	CO	0	16	4
Shaun Murphy	**5**	2011	CO	1	16	4
Li Hang	4	2011	CO	0	16	4
John Higgins	**5**	2011	CO	1	16	4
Ricky Walden	2	2011	CO	0	16	4
Mark Selby	**5**	2011	CO	1	16	4
Robert Milkins	1	2011	CO	0	16	4
Ali Carter	**5**	2011	CO	1	16	4
Marcus Campbell	3	2011	CO	0	16	4
Ding Junhui	**5**	2011	CO	1	16	4
Stephen Hendry	2	2011	CO	0	16	4
Stephen Lee	**5**	2011	CO	1	16	4
Ryan Day	2	2011	CO	0	16	4
Judd Trump	**5**	2011	CO	1	16	2
Peter Ebdon	1	2011	CO	0	16	2
Shaun Murphy	**5**	2011	CO	1	16	2
John Higgins	2	2011	CO	0	16	2
Mark Selby	**5**	2011	CO	1	16	2
Ali Carter	1	2011	CO	0	16	2
Ding Junhui	**5**	2011	CO	1	16	2
Stephen Lee	2	2011	CO	0	16	2
Judd Trump	**6**	2011	CO	1	16	1
Shaun Murphy	1	2011	CO	0	16	1
Mark Selby	**6**	2011	CO	1	16	1
Ding Junhui	3	2011	CO	0	16	1
Judd Trump	**10**	2011	CO	1	16	0.5
Mark Selby	8	2011	CO	0	16	0.5
Mark Selby	**5**	2011	SM	1	8	4
Jamie Cope	0	2011	SM	0	8	4
Shaun Murphy	**5**	2011	SM	1	8	4
Mark Allen	4	2011	SM	0	8	4
Mark King	**5**	2011	SM	1	8	4

Fergal O'Brien	3	2011	SM	0	8	4
Anthony Hamilton	**5**	2011	SM	1	8	4
Ronnie O'Sullivan	3	2011	SM	0	8	4
Mark Williams	**5**	2011	SM	1	8	4
Robert Milkins	1	2011	SM	0	8	4
Matthew Stevens	**5**	2011	SM	1	8	4
Martin Gould	1	2011	SM	0	8	4
Neil Robertson	**5**	2011	SM	1	8	4
Michael Holt	2	2011	SM	0	8	4
John Higgins	**5**	2011	SM	1	8	4
Stuart Bingham	2	2011	SM	0	8	4
Mark Selby	**5**	2011	SM	1	8	2
Shaun Murphy	4	2011	SM	0	8	2
Mark King	**5**	2011	SM	1	8	2
Anthony Hamilton	2	2011	SM	0	8	2
Mark Williams	**5**	2011	SM	1	8	2
Matthew Stevens	0	2011	SM	0	8	2
Neil Robertson	**5**	2011	SM	1	8	2
John Higgins	2	2011	SM	0	8	2
Mark Selby	**6**	2011	SM	1	8	1
Mark King	0	2011	SM	0	8	1
Mark Williams	**6**	2011	SM	1	8	1
Neil Robertson	5	2011	SM	0	8	1
Mark Selby	**10**	2011	SM	1	8	0.5
Mark Williams	9	2011	SM	0	8	0.5
Judd Trump	**6**	2011	UK	1	8	4
Ronnie O'Sullivan	5	2011	UK	0	8	4
Stephen Maguire	**6**	2011	UK	1	8	4
John Higgins	4	2011	UK	0	8	4
Neil Robertson	**6**	2011	UK	1	8	4
Graeme Dott	3	2011	UK	0	8	4
Ding Junhui	**6**	2011	UK	1	8	4
Matthew Stevens	5	2011	UK	0	8	4
Mark Allen	**6**	2011	UK	1	8	4
Ali Carter	2	2011	UK	0	8	4
Marco Fu	**6**	2011	UK	1	8	4
Mark Selby	3	2011	UK	0	8	4
Ricky Walden	**6**	2011	UK	1	8	4
Mark Williams	3	2011	UK	0	8	4
Shaun Murphy	**6**	2011	UK	1	8	4
Martin Gould	4	2011	UK	0	8	4
Judd Trump	**6**	2011	UK	1	8	2
Stephen Maguire	3	2011	UK	0	8	2
Neil Robertson	**6**	2011	UK	1	8	2
Ding Junhui	2	2011	UK	0	8	2
Mark Allen	**6**	2011	UK	1	8	2
Marco Fu	5	2011	UK	0	8	2
Ricky Walden	**6**	2011	UK	1	8	2

Shaun Murphy	3	2011	UK	0	8	2
Judd Trump	**9**	2011	UK	1	8	1
Neil Robertson	7	2011	UK	0	8	1
Mark Allen	**9**	2011	UK	1	8	1
Ricky Walden	7	2011	UK	0	8	1
Judd Trump	**10**	2011	UK	1	8	0.5
Mark Allen	8	2011	UK	0	8	0.5
John Higgins	**4**	2011	WO	1	16	4
Dave Harold	1	2011	WO	0	16	4
Matthew Stevens	**4**	2011	WO	1	16	4
Ryan Day	3	2011	WO	0	16	4
Ali Carter	**4**	2011	WO	1	16	4
Peter Ebdon	1	2011	WO	0	16	4
Ding Junhui	**4**	2011	WO	1	16	4
Mark Allen	3	2011	WO	0	16	4
Stephen Maguire	**4**	2011	WO	1	16	4
Stephen Hendry	2	2011	WO	0	16	4
Mark Williams	**4**	2011	WO	1	16	4
Jamie Cope	0	2011	WO	0	16	4
Mark Selby	**4**	2011	WO	1	16	4
Mark King	2	2011	WO	0	16	4
Graeme Dott	**4**	2011	WO	1	16	4
Neil Robertson	1	2011	WO	0	16	4
John Higgins	**5**	2011	WO	1	16	2
Matthew Stevens	3	2011	WO	0	16	2
Ali Carter	**5**	2011	WO	1	16	2
Ding Junhui	2	2011	WO	0	16	2
Stephen Maguire	**5**	2011	WO	1	16	2
Mark Williams	3	2011	WO	0	16	2
Mark Selby	**5**	2011	WO	1	16	2
Graeme Dott	3	2011	WO	0	16	2
John Higgins	**6**	2011	WO	1	16	1
Ali Carter	2	2011	WO	0	16	1
Stephen Maguire	**6**	2011	WO	1	16	1
Mark Selby	5	2011	WO	0	16	1
John Higgins	**9**	2011	WO	1	16	0.5
Stephen Maguire	6	2011	WO	0	16	0.5
John Higgins	**13**	2011	WC	1	8	4
Rory McLeod	7	2011	WC	0	8	4
Ronnie O'Sullivan	**13**	2011	WC	1	8	4
Shaun Murphy	10	2011	WC	0	8	4
Mark Williams	**13**	2011	WC	1	8	4
Jamie Cope	4	2011	WC	0	8	4
Mark Allen	**13**	2011	WC	1	8	4
Barry Hawkins	12	2011	WC	0	8	4
Judd Trump	**13**	2011	WC	1	8	4
Martin Gould	6	2011	WC	0	8	4
Graeme Dott	**13**	2011	WC	1	8	4

Ali Carter	11	2011	WC	0	8	4
Ding Junhui	**13**	2011	WC	1	8	4
Stuart Bingham	12	2011	WC	0	8	4
Mark Selby	**13**	2011	WC	1	8	4
Stephen Hendry	4	2011	WC	0	8	4
John Higgins	**13**	2011	WC	1	8	2
Ronnie O'Sullivan	10	2011	WC	0	8	2
Mark Williams	**13**	2011	WC	1	8	2
Mark Allen	5	2011	WC	0	8	2
Judd Trump	**13**	2011	WC	1	8	2
Graeme Dott	5	2011	WC	0	8	2
Ding Junhui	**13**	2011	WC	1	8	2
Mark Selby	10	2011	WC	0	8	2
John Higgins	**17**	2011	WC	1	8	1
Mark Williams	14	2011	WC	0	8	1
Judd Trump	**17**	2011	WC	1	8	1
Ding Junhui	15	2011	WC	0	8	1
John Higgins	**18**	2011	WC	1	8	0.5
Judd Trump	15	2011	WC	0	8	0.5

Data for 2012

Name	round	year	match	win	H	C
Peter Ebdon	**5**	2012	CO	1	16	4
John Higgins	4	2012	CO	0	16	4
Neil Robertson	**5**	2012	CO	1	16	4
Stephen Hendry	3	2012	CO	0	16	4
Ding Junhui	**0**	2012	CO	1	16	4
Mark Selby	0	2012	CO	0	16	4
Ali Carter	**5**	2012	CO	1	16	4
Lu Ning	1	2012	CO	0	16	4
Stephen Lee	**5**	2012	CO	1	16	4
Graeme Dott	3	2012	CO	0	16	4
Judd Trump	**5**	2012	CO	1	16	4
Stuart Bingham	3	2012	CO	0	16	4
Stephen Maguire	**5**	2012	CO	1	16	4
Ricky Walden	4	2012	CO	0	16	4
Ronnie O'Sullivan	**5**	2012	CO	1	16	4
Mark Williams	1	2012	CO	0	16	4
Peter Ebdon	**5**	2012	CO	1	16	2
Neil Robertson	3	2012	CO	0	16	2
Ding Junhui	**5**	2012	CO	1	16	2
Ali Carter	2	2012	CO	0	16	2
Stephen Lee	**5**	2012	CO	1	16	2
Judd Trump	3	2012	CO	0	16	2
Stephen Maguire	**5**	2012	CO	1	16	2
Ronnie O'Sullivan	4	2012	CO	0	16	2

Peter Ebdon	**6**	2012	CO	1	16	1
Ding Junhui	3	2012	CO	0	16	1
Stephen Maguire	**6**	2012	CO	1	16	1
Stephen Lee	2	2012	CO	0	16	1
Peter Ebdon	**10**	2012	CO	1	16	0.5
Stephen Maguire	9	2012	CO	0	16	0.5
John Higgins	**5**	2012	SM	1	8	4
Ryan Day	0	2012	SM	0	8	4
Ali Carter	**5**	2012	SM	1	8	4
Stephen Maguire	0	2012	SM	0	8	4
Shaun Murphy	**5**	2012	SM	1	8	4
Mark King	3	2012	SM	0	8	4
Stuart Bingham	**5**	2012	SM	1	8	4
Jamie Cope	1	2012	SM	0	8	4
Judd Trump	**5**	2012	SM	1	8	4
Mark Allen	2	2012	SM	0	8	4
Graeme Dott	**5**	2012	SM	1	8	4
Stephen Lee	1	2012	SM	0	8	4
Mark Williams	**5**	2012	SM	1	8	4
Ricky Walden	2	2012	SM	0	8	4
Joe Perry	**5**	2012	SM	1	8	4
Neil Robertson	0	2012	SM	0	8	4
John Higgins	**5**	2012	SM	1	8	2
Ali Carter	3	2012	SM	0	8	2
Shaun Murphy	**5**	2012	SM	1	8	2
Stuart Bingham	1	2012	SM	0	8	2
Judd Trump	**5**	2012	SM	1	8	2
Graeme Dott	4	2012	SM	0	8	2
Mark Williams	**5**	2012	SM	1	8	2
Joe Perry	4	2012	SM	0	8	2
John Higgins	**6**	2012	SM	1	8	1
Shaun Murphy	3	2012	SM	0	8	1
Judd Trump	**6**	2012	SM	1	8	1
Mark Williams	4	2012	SM	0	8	1
John Higgins	**10**	2012	SM	1	8	0.5
Judd Trump	9	2012	SM	0	8	0.5
Mark Selby	**6**	2012	UK	1	8	4
Ryan Day	4	2012	UK	0	8	4
Neil Robertson	**6**	2012	UK	1	8	4
Barry Hawkins	2	2012	UK	0	8	4
Mark Davis	**6**	2012	UK	1	8	4
John Higgins	5	2012	UK	0	8	4
Matthew Stevens	**6**	2012	UK	1	8	4
Marco Fu	4	2012	UK	0	8	4
Shaun Murphy	**6**	2012	UK	1	8	4
Graeme Dott	2	2012	UK	0	8	4
Luca Brecel	**6**	2012	UK	1	8	4
Mark King	4	2012	UK	0	8	4

Ali Carter	**6**	2012	UK	1	8	4
Mark Joyce	2	2012	UK	0	8	4
Stuart Bingham	**6**	2012	UK	1	8	4
Stephen Maguire	4	2012	UK	0	8	4
Mark Selby	**6**	2012	UK	1	8	2
Neil Robertson	4	2012	UK	0	8	2
Mark Davis	**6**	2012	UK	1	8	2
Matthew Stevens	4	2012	UK	0	8	2
Shaun Murphy	**6**	2012	UK	1	8	2
Luca Brecel	5	2012	UK	0	8	2
Ali Carter	**6**	2012	UK	1	8	2
Stuart Bingham	4	2012	UK	0	8	2
Mark Selby	**9**	2012	UK	1	8	1
Mark Davis	4	2012	UK	0	8	1
Shaun Murphy	**9**	2012	UK	1	8	1
Ali Carter	8	2012	UK	0	8	1
Mark Selby	**10**	2012	UK	1	8	0.5
Shaun Murphy	6	2012	UK	0	8	0.5
Ding Junhui	**4**	2012	WO	1	16	4
John Higgins	3	2012	WO	0	16	4
Stephen Lee	**4**	2012	WO	1	16	4
Tom Ford	1	2012	WO	0	16	4
Shaun Murphy	**4**	2012	WO	1	16	4
Steve Davis	0	2012	WO	0	16	4
Mark Allen	**4**	2012	WO	1	16	4
Stephen Hendry	0	2012	WO	0	16	4
Mark Selby	**4**	2012	WO	1	16	4
Martin Gould	1	2012	WO	0	16	4
Stephen Maguire	**4**	2012	WO	1	16	4
Matthew Stevens	2	2012	WO	0	16	4
Ronnie O'Sullivan	**4**	2012	WO	1	16	4
Mark Williams	1	2012	WO	0	16	4
Judd Trump	**4**	2012	WO	1	16	4
Stuart Bingham	1	2012	WO	0	16	4
Ding Junhui	**5**	2012	WO	1	16	2
Stephen Lee	4	2012	WO	0	16	2
Shaun Murphy	**5**	2012	WO	1	16	2
Mark Allen	4	2012	WO	0	16	2
Mark Selby	**5**	2012	WO	1	16	2
Stephen Maguire	3	2012	WO	0	16	2
Ronnie O'Sullivan	**5**	2012	WO	1	16	2
Judd Trump	3	2012	WO	0	16	2
Ding Junhui	**6**	2012	WO	1	16	1
Shaun Murphy	2	2012	WO	0	16	1
Mark Selby	**6**	2012	WO	1	16	1
Ronnie O'Sullivan	2	2012	WO	0	16	1
Ding Junhui	**9**	2012	WO	1	16	0.5
Mark Selby	6	2012	WO	0	16	0.5

Ronnie O'Sullivan	**13**	2012	WC	1	8	4
Mark Williams	6	2012	WC	0	8	4
Neil Robertson	**13**	2012	WC	1	8	4
David Gilbert	9	2012	WC	0	8	4
Matthew Stevens	**13**	2012	WC	1	8	4
Barry Hawkins	11	2012	WC	0	8	4
Ryan Day	**13**	2012	WC	1	8	4
Cao Yupeng	7	2012	WC	0	8	4
Ali Carter	**13**	2012	WC	1	8	4
Judd Trump	12	2012	WC	0	8	4
Jamie Jones	**13**	2012	WC	1	8	4
Andrew Higginson	10	2012	WC	0	8	4
Stephen Maguire	**13**	2012	WC	1	8	4
Joe Perry	7	2012	WC	0	8	4
Stephen Hendry	**13**	2012	WC	1	8	4
John Higgins	4	2012	WC	0	8	4
Ronnie O'Sullivan	**13**	2012	WC	1	8	2
Neil Robertson	10	2012	WC	0	8	2
Matthew Stevens	**13**	2012	WC	1	8	2
Ryan Day	5	2012	WC	0	8	2
Ali Carter	**13**	2012	WC	1	8	2
Jamie Jones	11	2012	WC	0	8	2
Stephen Maguire	**13**	2012	WC	1	8	2
Stephen Hendry	2	2012	WC	0	8	2
Ronnie O'Sullivan	**17**	2012	WC	1	8	1
Matthew Stevens	10	2012	WC	0	8	1
Ali Carter	**17**	2012	WC	1	8	1
Stephen Maguire	12	2012	WC	0	8	1
Ronnie O'Sullivan	**18**	2012	WC	1	8	0.5
Ali Carter	11	2012	WC	0	8	0.5

Data for 2013

Name	round	year	match	win	H	C
Mark Williams	**5**	2013	CO	1	16	4
Ali Carter	4	2013	CO	0	16	4
Mark Selby	**5**	2013	CO	1	16	4
Ricky Walden	2	2013	CO	0	16	4
Neil Robertson	**5**	2013	CO	1	16	4
Mark Allen	1	2013	CO	0	16	4
Shaun Murphy	**5**	2013	CO	1	16	4
Rory McLeod	3	2013	CO	0	16	4
Stephen Maguire	**5**	2013	CO	1	16	4
Barry Hawkins	1	2013	CO	0	16	4
Jack Lisowski	**5**	2013	CO	1	16	4
Mark Davis	4	2013	CO	0	16	4
Marcus Campbell	**5**	2013	CO	1	16	4

Graeme Dott	4	2013	CO	0	16	4
Stuart Bingham	**5**	2013	CO	1	16	4
Robert Milkins	3	2013	CO	0	16	4
Mark Selby	**5**	2013	CO	1	16	2
Mark Williams	1	2013	CO	0	16	2
Neil Robertson	**5**	2013	CO	1	16	2
Marcus Campbell	2	2013	CO	0	16	2
Shaun Murphy	**5**	2013	CO	1	16	2
Jack Lisowski	4	2013	CO	0	16	2
Stephen Maguire	**5**	2013	CO	1	16	2
Stuart Bingham	1	2013	CO	0	16	2
Mark Selby	**6**	2013	CO	1	16	1
Shaun Murphy	2	2013	CO	0	16	1
Neil Robertson	**6**	2013	CO	1	16	1
Stephen Maguire	5	2013	CO	0	16	1
Neil Robertson	**10**	2013	CO	1	16	0.5
Mark Selby	6	2013	CO	0	16	0.5
Kyren Wilson	**5**	2013	SM	1	8	4
Marco Fu	3	2013	SM	0	8	4
Mark Selby	**5**	2013	SM	1	8	4
Robert Milkins	4	2013	SM	0	8	4
Neil Robertson	**5**	2013	SM	1	8	4
Mark King	3	2013	SM	0	8	4
Ding Junhui	**5**	2013	SM	1	8	4
Shaun Murphy	4	2013	SM	0	8	4
Michael Holt	**5**	2013	SM	1	8	4
Martin Gould	4	2013	SM	0	8	4
Barry Hawkins	**5**	2013	SM	1	8	4
Ryan Day	2	2013	SM	0	8	4
Xiao Guodong	**5**	2013	SM	1	8	4
Peter Lines	3	2013	SM	0	8	4
Mark Davis	**5**	2013	SM	1	8	4
John Higgins	1	2013	SM	0	8	4
Ding Junhui	**5**	2013	SM	1	8	2
Neil Robertson	2	2013	SM	0	8	2
Michael Holt	**5**	2013	SM	1	8	2
Kyren Wilson	1	2013	SM	0	8	2
Barry Hawkins	**5**	2013	SM	1	8	2
Mark Selby	4	2013	SM	0	8	2
Xiao Guodong	**5**	2013	SM	1	8	2
Mark Davis	4	2013	SM	0	8	2
Ding Junhui	**6**	2013	SM	1	8	1
Barry Hawkins	2	2013	SM	0	8	1
Xiao Guodong	**6**	2013	SM	1	8	1
Michael Holt	3	2013	SM	0	8	1
Ding Junhui	**10**	2013	SM	1	8	0.5
Xiao Guodong	6	2013	SM	0	8	0.5
Ricky Walden	**6**	2013	UK	1	8	4

Ding Junhui	4	2013	UK	0	8	4
Mark Selby	**6**	2013	UK	1	8	4
Graeme Dott	2	2013	UK	0	8	4
Neil Robertson	**6**	2013	UK	1	8	4
Joe Perry	1	2013	UK	0	8	4
Ronnie O'Sullivan	**6**	2013	UK	1	8	4
Robert Milkins	0	2013	UK	0	8	4
Stephen Maguire	**6**	2013	UK	1	8	4
John Higgins	3	2013	UK	0	8	4
Barry Hawkins	**6**	2013	UK	1	8	4
Shaun Murphy	5	2013	UK	0	8	4
Stuart Bingham	**6**	2013	UK	1	8	4
David Morris	1	2013	UK	0	8	4
Mark Allen	**6**	2013	UK	1	8	4
Judd Trump	4	2013	UK	0	8	4
Ricky Walden	**6**	2013	UK	1	8	2
Mark Allen	2	2013	UK	0	8	2
Mark Selby	**6**	2013	UK	1	8	2
Barry Hawkins	5	2013	UK	0	8	2
Neil Robertson	**6**	2013	UK	1	8	2
Stephen Maguire	2	2013	UK	0	8	2
Stuart Bingham	**6**	2013	UK	1	8	2
Ronnie O'Sullivan	4	2013	UK	0	8	2
Mark Selby	**9**	2013	UK	1	8	1
Ricky Walden	5	2013	UK	0	8	1
Neil Robertson	**9**	2013	UK	1	8	1
Stuart Bingham	8	2013	UK	0	8	1
Neil Robertson	**10**	2013	UK	1	8	0.5
Mark Selby	7	2013	UK	0	8	0.5
Judd Trump	**4**	2013	WO	1	16	4
Andrew Higginson	1	2013	WO	0	16	4
Robert Milkins	**4**	2013	WO	1	16	4
Sam Baird	2	2013	WO	0	16	4
Alan McManus	**4**	2013	WO	1	16	4
Joe Perry	3	2013	WO	0	16	4
Stephen Maguire	**4**	2013	WO	1	16	4
Matthew Stevens	2	2013	WO	0	16	4
Ding Junhui	**4**	2013	WO	1	16	4
Mark Allen	2	2013	WO	0	16	4
Ken Doherty	**4**	2013	WO	1	16	4
Tom Ford	3	2013	WO	0	16	4
Stuart Bingham	**4**	2013	WO	1	16	4
Neil Robertson	3	2013	WO	0	16	4
Pankaj Advani	**4**	2013	WO	1	16	4
Graeme Dott	1	2013	WO	0	16	4
Judd Trump	**5**	2013	WO	1	16	2
Pankaj Advani	2	2013	WO	0	16	2
Stephen Maguire	**5**	2013	WO	1	16	2

Alan McManus	3	2013	WO	0	16	2
Ding Junhui	**5**	2013	WO	1	16	2
Robert Milkins	1	2013	WO	0	16	2
Stuart Bingham	**5**	2013	WO	1	16	2
Ken Doherty	3	2013	WO	0	16	2
Stephen Maguire	**6**	2013	WO	1	16	1
Judd Trump	4	2013	WO	0	16	1
Stuart Bingham	**6**	2013	WO	1	16	1
Ding Junhui	5	2013	WO	0	16	1
Stephen Maguire	**9**	2013	WO	1	16	0.5
Stuart Bingham	8	2013	WO	0	16	0.5
Michael White	**13**	2013	WC	1	8	4
Dechawat Poomjaeng	3	2013	WC	0	8	4
Ricky Walden	**13**	2013	WC	1	8	4
Robert Milkins	11	2013	WC	0	8	4
Judd Trump	**13**	2013	WC	1	8	4
Marco Fu	7	2013	WC	0	8	4
Ronnie O'Sullivan	**13**	2013	WC	1	8	4
Ali Carter	8	2013	WC	0	8	4
Shaun Murphy	**13**	2013	WC	1	8	4
Graeme Dott	11	2013	WC	0	8	4
Ding Junhui	**13**	2013	WC	1	8	4
Mark King	9	2013	WC	0	8	4
Barry Hawkins	**13**	2013	WC	1	8	4
Mark Selby	10	2013	WC	0	8	4
Stuart Bingham	**13**	2013	WC	1	8	4
Mark Davis	10	2013	WC	0	8	4
Ricky Walden	**13**	2013	WC	1	8	2
Michael White	6	2013	WC	0	8	2
Judd Trump	**13**	2013	WC	1	8	2
Shaun Murphy	12	2013	WC	0	8	2
Ronnie O'Sullivan	**13**	2013	WC	1	8	2
Stuart Bingham	4	2013	WC	0	8	2
Barry Hawkins	**13**	2013	WC	1	8	2
Ding Junhui	7	2013	WC	0	8	2
Ronnie O'Sullivan	**17**	2013	WC	1	8	1
Judd Trump	11	2013	WC	0	8	1
Barry Hawkins	**17**	2013	WC	1	8	1
Ricky Walden	14	2013	WC	0	8	1
Ronnie O'Sullivan	**18**	2013	WC	1	8	0.5
Barry Hawkins	12	2013	WC	0	8	0.5

Data for 2014

Name	round	year	match	win	H	C
Ricky Walden	**5**	2014	CO	1	16	4
Shaun Murphy	3	2014	CO	0	16	4

Mark Selby	**5**	2014	CO	1	16	4
Jimmy White	1	2014	CO	0	16	4
Neil Robertson	**5**	2014	CO	1	16	4
Yu Delu	4	2014	CO	0	16	4
Mark King	**5**	2014	CO	1	16	4
Jamie O'Neill	3	2014	CO	0	16	4
Ding Junhui	**5**	2014	CO	1	16	4
John Higgins	2	2014	CO	0	16	4
Mike Dunn	**5**	2014	CO	1	16	4
Craig Steadman	3	2014	CO	0	16	4
Graeme Dott	**5**	2014	CO	1	16	4
Luca Brecel	2	2014	CO	0	16	4
Ali Carter	**5**	2014	CO	1	16	4
Peter Ebdon	3	2014	CO	0	16	4
Neil Robertson	**5**	2014	CO	1	16	2
Graeme Dott	3	2014	CO	0	16	2
Ding Junhui	**5**	2014	CO	1	16	2
Mark King	2	2014	CO	0	16	2
Mike Dunn	**5**	2014	CO	1	16	2
Mark Selby	3	2014	CO	0	16	2
Ali Carter	**5**	2014	CO	1	16	2
Ricky Walden	3	2014	CO	0	16	2
Neil Robertson	**6**	2014	CO	1	16	1
Ali Carter	2	2014	CO	0	16	1
Ding Junhui	**6**	2014	CO	1	16	1
Mike Dunn	0	2014	CO	0	16	1
Ding Junhui	**10**	2014	CO	1	16	0.5
Neil Robertson	5	2014	CO	0	16	0.5
Michael White	**5**	2014	SM	1	8	4
Ryan Day	2	2014	SM	0	8	4
Mark Selby	**5**	2014	SM	1	8	4
Michael Holt	3	2014	SM	0	8	4
Fergal O'Brien	**5**	2014	SM	1	8	4
Zhao Xintong	3	2014	SM	0	8	4
Alan McManus	**5**	2014	SM	1	8	4
Stephen Maguire	1	2014	SM	0	8	4
Ding Junhui	**5**	2014	SM	1	8	4
Martin Gould	3	2014	SM	0	8	4
Graeme Dott	**5**	2014	SM	1	8	4
Shaun Murphy	3	2014	SM	0	8	4
Stuart Bingham	**5**	2014	SM	1	8	4
Dominic Dale	1	2014	SM	0	8	4
Mark Allen	**5**	2014	SM	1	8	4
Mark Williams	1	2014	SM	0	8	4
Mark Selby	**5**	2014	SM	1	8	2
Fergal O'Brien	0	2014	SM	0	8	2
Ding Junhui	**5**	2014	SM	1	8	2
Graeme Dott	2	2014	SM	0	8	2

Stuart Bingham	**5**	2014	SM	1	8	2
Alan McManus	1	2014	SM	0	8	2
Mark Allen	**5**	2014	SM	1	8	2
Michael White	4	2014	SM	0	8	2
Stuart Bingham	**6**	2014	SM	1	8	1
Ding Junhui	4	2014	SM	0	8	1
Mark Allen	**6**	2014	SM	1	8	1
Mark Selby	5	2014	SM	0	8	1
Stuart Bingham	**10**	2014	SM	1	8	0.5
Mark Allen	3	2014	SM	0	8	0.5
Judd Trump	**6**	2014	UK	1	8	4
Rod Lawler	3	2014	UK	0	8	4
Ronnie O'Sullivan	**6**	2014	UK	1	8	4
Matthew Selt	0	2014	UK	0	8	4
Anthony McGill	**6**	2014	UK	1	8	4
John Higgins	5	2014	UK	0	8	4
Stephen Maguire	**6**	2014	UK	1	8	4
David Morris	3	2014	UK	0	8	4
Marco Fu	**6**	2014	UK	1	8	4
Shaun Murphy	5	2014	UK	0	8	4
Graeme Dott	**6**	2014	UK	1	8	4
Neil Robertson	5	2014	UK	0	8	4
Mark Davis	**6**	2014	UK	1	8	4
James Cahill	2	2014	UK	0	8	4
Stuart Bingham	**6**	2014	UK	1	8	4
Ricky Walden	0	2014	UK	0	8	4
Judd Trump	**6**	2014	UK	1	8	2
Mark Davis	1	2014	UK	0	8	2
Ronnie O'Sullivan	**6**	2014	UK	1	8	2
Anthony McGill	4	2014	UK	0	8	2
Stephen Maguire	**6**	2014	UK	1	8	2
Marco Fu	4	2014	UK	0	8	2
Stuart Bingham	**6**	2014	UK	1	8	2
Graeme Dott	5	2014	UK	0	8	2
Judd Trump	**6**	2014	UK	1	8	1
Stephen Maguire	4	2014	UK	0	8	1
Ronnie O'Sullivan	**6**	2014	UK	1	8	1
Stuart Bingham	5	2014	UK	0	8	1
Ronnie O'Sullivan	**10**	2014	UK	1	8	0.5
Judd Trump	9	2014	UK	0	8	0.5
Joel Walker	**4**	2014	WO	1	16	4
Stephen Maguire	3	2014	WO	0	16	4
Mark Selby	**4**	2014	WO	1	16	4
Ali Carter	1	2014	WO	0	16	4
Joe Perry	**4**	2014	WO	1	16	4
Stuart Bingham	3	2014	WO	0	16	4
Ronnie O'Sullivan	**4**	2014	WO	1	16	4
Ricky Walden	1	2014	WO	0	16	4

Ding Junhui	**4**	2014	WO	1	16	4
Scott Donaldson	0	2014	WO	0	16	4
John Higgins	**4**	2014	WO	1	16	4
Judd Trump	3	2014	WO	0	16	4
Barry Hawkins	**4**	2014	WO	1	16	4
Liang Wenbo	2	2014	WO	0	16	4
Marco Fu	**4**	2014	WO	1	16	4
Mark Williams	2	2014	WO	0	16	4
Joe Perry	**5**	2014	WO	1	16	2
Mark Selby	1	2014	WO	0	16	2
Ronnie O'Sullivan	**5**	2014	WO	1	16	2
John Higgins	1	2014	WO	0	16	2
Ding Junhui	**5**	2014	WO	1	16	2
Joel Walker	4	2014	WO	0	16	2
Barry Hawkins	**5**	2014	WO	1	16	2
Marco Fu	0	2014	WO	0	16	2
Ronnie O'Sullivan	**6**	2014	WO	1	16	1
Barry Hawkins	2	2014	WO	0	16	1
Ding Junhui	**6**	2014	WO	1	16	1
Joe Perry	4	2014	WO	0	16	1
Ronnie O'Sullivan	**9**	2014	WO	1	16	0.5
Ding Junhui	3	2014	WO	0	16	0.5
Judd Trump	**13**	2014	WC	1	8	4
Ryan Day	7	2014	WC	0	8	4
Mark Selby	**13**	2014	WC	1	8	4
Ali Carter	9	2014	WC	0	8	4
Neil Robertson	**13**	2014	WC	1	8	4
Mark Allen	7	2014	WC	0	8	4
Ronnie O'Sullivan	**13**	2014	WC	1	8	4
Joe Perry	11	2014	WC	0	8	4
Shaun Murphy	**13**	2014	WC	1	8	4
Marco Fu	8	2014	WC	0	8	4
Alan McManus	**13**	2014	WC	1	8	4
Ken Doherty	8	2014	WC	0	8	4
Barry Hawkins	**13**	2014	WC	1	8	4
Ricky Walden	11	2014	WC	0	8	4
Dominic Dale	**13**	2014	WC	1	8	4
Michael Wasley	4	2014	WC	0	8	4
Mark Selby	**13**	2014	WC	1	8	2
Alan McManus	5	2014	WC	0	8	2
Neil Robertson	**13**	2014	WC	1	8	2
Judd Trump	11	2014	WC	0	8	2
Ronnie O'Sullivan	**13**	2014	WC	1	8	2
Shaun Murphy	3	2014	WC	0	8	2
Barry Hawkins	**13**	2014	WC	1	8	2
Dominic Dale	12	2014	WC	0	8	2
Mark Selby	**17**	2014	WC	1	8	1
Neil Robertson	15	2014	WC	0	8	1

Ronnie O'Sullivan	**17**	2014	WC	1	8	1
Barry Hawkins	7	2014	WC	0	8	1
Mark Selby	**18**	2014	WC	1	8	0.5
Ronnie O'Sullivan	14	2014	WC	0	8	0.5

Data for 2015

Name	round	year	match	win	H	C
Gary Wilson	**5**	2015	CO	1	16	4
Dechawat Poomjaeng	1	2015	CO	0	16	4
Mark Selby	**5**	2015	CO	1	16	4
David Gilbert	2	2015	CO	0	16	4
Shaun Murphy	**5**	2015	CO	1	16	4
Jamie Jones	3	2015	CO	0	16	4
Robert Milkins	**5**	2015	CO	1	16	4
Michael White	1	2015	CO	0	16	4
Kurt Maflin	**5**	2015	CO	1	16	4
Robin Hull	1	2015	CO	0	16	4
Ding Junhui	**5**	2015	CO	1	16	4
Mark Williams	2	2015	CO	0	16	4
John Higgins	**5**	2015	CO	1	16	4
Judd Trump	4	2015	CO	0	16	4
Barry Hawkins	**5**	2015	CO	1	16	4
Stephen Maguire	3	2015	CO	0	16	4
Gary Wilson	**5**	2015	CO	1	16	2
Barry Hawkins	3	2015	CO	0	16	2
Mark Selby	**5**	2015	CO	1	16	2
Robert Milkins	4	2015	CO	0	16	2
Kurt Maflin	**5**	2015	CO	1	16	2
Shaun Murphy	4	2015	CO	0	16	2
Ding Junhui	**5**	2015	CO	1	16	2
John Higgins	4	2015	CO	0	16	2
Gary Wilson	**6**	2015	CO	1	16	1
Ding Junhui	5	2015	CO	0	16	1
Mark Selby	**6**	2015	CO	1	16	1
Kurt Maflin	3	2015	CO	0	16	1
Mark Selby	**10**	2015	CO	1	16	0.5
Gary Wilson	2	2015	CO	0	16	0.5
Kyren Wilson	**5**	2015	SM	1	8	4
Michael Holt	1	2015	SM	0	8	4
Mark Williams	**5**	2015	SM	1	8	4
Jamie Cope	3	2015	SM	0	8	4
Judd Trump	**5**	2015	SM	1	8	4
Matthew Selt	4	2015	SM	0	8	4
Ding Junhui	**5**	2015	SM	1	8	4
Ryan Day	4	2015	SM	0	8	4
Martin Gould	**5**	2015	SM	1	8	4

John Higgins	3	2015	SM	0	8	4
Mark Davis	**5**	2015	SM	1	8	4
Shaun Murphy	3	2015	SM	0	8	4
Stuart Bingham	**5**	2015	SM	1	8	4
Mike Dunn	1	2015	SM	0	8	4
Mark Allen	**5**	2015	SM	1	8	4
David Grace	1	2015	SM	0	8	4
Kyren Wilson	**5**	2015	SM	1	8	2
Ding Junhui	4	2015	SM	0	8	2
Judd Trump	**5**	2015	SM	1	8	2
Mark Williams	1	2015	SM	0	8	2
Stuart Bingham	**5**	2015	SM	1	8	2
Martin Gould	4	2015	SM	0	8	2
Mark Allen	**5**	2015	SM	1	8	2
Mark Davis	1	2015	SM	0	8	2
Kyren Wilson	**6**	2015	SM	1	8	1
Mark Allen	1	2015	SM	0	8	1
Judd Trump	**6**	2015	SM	1	8	1
Stuart Bingham	3	2015	SM	0	8	1
Kyren Wilson	**10**	2015	SM	1	8	0.5
Judd Trump	9	2015	SM	0	8	0.5
Liang Wenbo	**6**	2015	UK	1	8	4
Tom Ford	5	2015	UK	0	8	4
Matthew Selt	**6**	2015	UK	1	8	4
Luca Brecel	4	2015	UK	0	8	4
Mark Selby	**6**	2015	UK	1	8	4
Dechawat Poomjaeng	1	2015	UK	0	8	4
Neil Robertson	**6**	2015	UK	1	8	4
Stephen Maguire	1	2015	UK	0	8	4
John Higgins	**6**	2015	UK	1	8	4
Jamie Burnett	4	2015	UK	0	8	4
David Grace	**6**	2015	UK	1	8	4
Peter Ebdon	2	2015	UK	0	8	4
Martin Gould	**6**	2015	UK	1	8	4
Joe Swail	3	2015	UK	0	8	4
Marco Fu	**6**	2015	UK	1	8	4
Shaun Murphy	4	2015	UK	0	8	4
Liang Wenbo	**6**	2015	UK	1	8	2
Marco Fu	5	2015	UK	0	8	2
Mark Selby	**6**	2015	UK	1	8	2
Matthew Selt	1	2015	UK	0	8	2
Neil Robertson	**6**	2015	UK	1	8	2
John Higgins	5	2015	UK	0	8	2
David Grace	**6**	2015	UK	1	8	2
Martin Gould	5	2015	UK	0	8	2
Liang Wenbo	**6**	2015	UK	1	8	1
David Grace	4	2015	UK	0	8	1
Neil Robertson	**6**	2015	UK	1	8	1

Mark Selby	0	2015	UK	0	8	1
Neil Robertson	**10**	2015	UK	1	8	0.5
Liang Wenbo	5	2015	UK	0	8	0.5
Ben Woollaston	**4**	2015	WO	1	16	4
Ali Carter	2	2015	WO	0	16	4
Gary Wilson	**4**	2015	WO	1	16	4
Neil Robertson	2	2015	WO	0	16	4
Mark Williams	**4**	2015	WO	1	16	4
Judd Trump	1	2015	WO	0	16	4
Ricky Walden	**4**	2015	WO	1	16	4
Stuart Bingham	2	2015	WO	0	16	4
Stephen Maguire	**4**	2015	WO	1	16	4
Alan McManus	0	2015	WO	0	16	4
John Higgins	**4**	2015	WO	1	16	4
Michael Georgiou	2	2015	WO	0	16	4
Marco Fu	**4**	2015	WO	1	16	4
Matthew Stevens	2	2015	WO	0	16	4
Luca Brecel	**4**	2015	WO	1	16	4
Mark Selby	3	2015	WO	0	16	4
Ben Woollaston	**5**	2015	WO	1	16	2
Gary Wilson	2	2015	WO	0	16	2
Mark Williams	**5**	2015	WO	1	16	2
Marco Fu	1	2015	WO	0	16	2
John Higgins	**5**	2015	WO	1	16	2
Stephen Maguire	1	2015	WO	0	16	2
Luca Brecel	**5**	2015	WO	1	16	2
Ricky Walden	3	2015	WO	0	16	2
Ben Woollaston	**6**	2015	WO	1	16	1
Mark Williams	5	2015	WO	0	16	1
John Higgins	**6**	2015	WO	1	16	1
Luca Brecel	4	2015	WO	0	16	1
John Higgins	**9**	2015	WO	1	16	0.5
Ben Woollaston	3	2015	WO	0	16	0.5
Judd Trump	**13**	2015	WC	1	8	4
Marco Fu	8	2015	WC	0	8	4
Neil Robertson	**13**	2015	WC	1	8	4
Ali Carter	5	2015	WC	0	8	4
Ronnie O'Sullivan	**13**	2015	WC	1	8	4
Matthew Stevens	5	2015	WC	0	8	4
Shaun Murphy	**13**	2015	WC	1	8	4
Joe Perry	5	2015	WC	0	8	4
Anthony McGill	**13**	2015	WC	1	8	4
Mark Selby	9	2015	WC	0	8	4
Ding Junhui	**13**	2015	WC	1	8	4
John Higgins	9	2015	WC	0	8	4
Barry Hawkins	**13**	2015	WC	1	8	4
Mark Allen	11	2015	WC	0	8	4
Stuart Bingham	**13**	2015	WC	1	8	4

Graeme Dott	5	2015	WC	0	8	4
Judd Trump	**13**	2015	WC	1	8	2
Ding Junhui	4	2015	WC	0	8	2
Shaun Murphy	**13**	2015	WC	1	8	2
Anthony McGill	11	2015	WC	0	8	2
Barry Hawkins	**13**	2015	WC	1	8	2
Neil Robertson	12	2015	WC	0	8	2
Stuart Bingham	**13**	2015	WC	1	8	2
Ronnie O'Sullivan	9	2015	WC	0	8	2
Shaun Murphy	**17**	2015	WC	1	8	1
Barry Hawkins	9	2015	WC	0	8	1
Stuart Bingham	**17**	2015	WC	1	8	1
Judd Trump	16	2015	WC	0	8	1
Stuart Bingham	**18**	2015	WC	1	8	0.5
Shaun Murphy	15	2015	WC	0	8	0.5

Data for 2016

Name	round	year	match	win	H	C
Ricky Walden	**5**	2016	CO	1	16	4
Tian Pengfei	4	2016	CO	0	16	4
Judd Trump	**5**	2016	CO	1	16	4
Marco Fu	1	2016	CO	0	16	4
Noppon Saengkham	**5**	2016	CO	1	16	4
Graeme Dott	1	2016	CO	0	16	4
Stephen Maguire	**5**	2016	CO	1	16	4
Dominic Dale	1	2016	CO	0	16	4
Mark King	**5**	2016	CO	1	16	4
Martin O'Donnell	0	2016	CO	0	16	4
John Higgins	**5**	2016	CO	1	16	4
David Gilbert	3	2016	CO	0	16	4
Alfie Burden	**5**	2016	CO	1	16	4
Rory McLeod	1	2016	CO	0	16	4
Stuart Bingham	**5**	2016	CO	1	16	4
Rod Lawler	2	2016	CO	0	16	4
Judd Trump	**5**	2016	CO	1	16	2
Mark King	3	2016	CO	0	16	2
Stephen Maguire	**5**	2016	CO	1	16	2
Alfie Burden	1	2016	CO	0	16	2
John Higgins	**5**	2016	CO	1	16	2
Noppon Saengkham	3	2016	CO	0	16	2
Ricky Walden	**5**	2016	CO	1	16	2
Stuart Bingham	1	2016	CO	0	16	2
Ricky Walden	**6**	2016	CO	1	16	1
John Higgins	5	2016	CO	0	16	1
Judd Trump	**6**	2016	CO	1	16	1
Stephen Maguire	0	2016	CO	0	16	1

Judd Trump	**10**	2016	CO	1	16	0.5
Ricky Walden	4	2016	CO	0	16	0.5
Michael White	**5**	2016	SM	1	8	4
Judd Trump	3	2016	SM	0	8	4
Mark Selby	**5**	2016	SM	1	8	4
Stuart Carrington	3	2016	SM	0	8	4
Stephen Maguire	**5**	2016	SM	1	8	4
Barry Hawkins	3	2016	SM	0	8	4
Ding Junhui	**5**	2016	SM	1	8	4
Mark Allen	2	2016	SM	0	8	4
Michael Holt	**5**	2016	SM	1	8	4
Ronnie O'Sullivan	2	2016	SM	0	8	4
Ryan Day	**5**	2016	SM	1	8	4
Mei Xinwen	2	2016	SM	0	8	4
Ali Carter	**5**	2016	SM	1	8	4
John Higgins	2	2016	SM	0	8	4
Stuart Bingham	**5**	2016	SM	1	8	4
David Gilbert	2	2016	SM	0	8	4
Mark Selby	**5**	2016	SM	1	8	2
Ryan Day	3	2016	SM	0	8	2
Stephen Maguire	**5**	2016	SM	1	8	2
Michael White	1	2016	SM	0	8	2
Ding Junhui	**5**	2016	SM	1	8	2
Michael Holt	3	2016	SM	0	8	2
Stuart Bingham	**5**	2016	SM	1	8	2
Ali Carter	1	2016	SM	0	8	2
Mark Selby	**6**	2016	SM	1	8	1
Stuart Bingham	5	2016	SM	0	8	1
Ding Junhui	**6**	2016	SM	1	8	1
Stephen Maguire	3	2016	SM	0	8	1
Ding Junhui	**10**	2016	SM	1	8	0.5
Mark Selby	6	2016	SM	0	8	0.5
Mark Williams	**6**	2016	UK	1	8	4
Liam Highfield	5	2016	UK	0	8	4
Mark Selby	**6**	2016	UK	1	8	4
Zhang Anda	1	2016	UK	0	8	4
Ronnie O'Sullivan	**6**	2016	UK	1	8	4
Matthew Stevens	2	2016	UK	0	8	4
Shaun Murphy	**6**	2016	UK	1	8	4
Zhou Yuelong	2	2016	UK	0	8	4
Jamie Jones	**6**	2016	UK	1	8	4
David Gilbert	2	2016	UK	0	8	4
John Higgins	**6**	2016	UK	1	8	4
Mark Allen	3	2016	UK	0	8	4
Marco Fu	**6**	2016	UK	1	8	4
Oliver Lines	0	2016	UK	0	8	4
Luca Brecel	**6**	2016	UK	1	8	4
Stephen Maguire	3	2016	UK	0	8	4

Mark Selby	**6**	2016	UK	1	8	2
John Higgins	5	2016	UK	0	8	2
Ronnie O'Sullivan	**6**	2016	UK	1	8	2
Mark Williams	2	2016	UK	0	8	2
Shaun Murphy	**6**	2016	UK	1	8	2
Luca Brecel	1	2016	UK	0	8	2
Marco Fu	**6**	2016	UK	1	8	2
Jamie Jones	5	2016	UK	0	8	2
Mark Selby	**6**	2016	UK	1	8	1
Shaun Murphy	2	2016	UK	0	8	1
Ronnie O'Sullivan	**6**	2016	UK	1	8	1
Marco Fu	5	2016	UK	0	8	1
Mark Selby	**10**	2016	UK	1	8	0.5
Ronnie O'Sullivan	7	2016	UK	0	8	0.5
Ben Woollaston	**4**	2016	WO	1	16	4
Martin Gould	1	2016	WO	0	16	4
Michael White	**4**	2016	WO	1	16	4
John Higgins	1	2016	WO	0	16	4
Mark Selby	**4**	2016	WO	1	16	4
Mark Williams	2	2016	WO	0	16	4
Neil Robertson	**4**	2016	WO	1	16	4
Marco Fu	2	2016	WO	0	16	4
Joe Perry	**4**	2016	WO	1	16	4
Judd Trump	3	2016	WO	0	16	4
Ronnie O'Sullivan	**4**	2016	WO	1	16	4
Yu Delu	1	2016	WO	0	16	4
Ding Junhui	**4**	2016	WO	1	16	4
Luca Brecel	2	2016	WO	0	16	4
Mark Allen	**4**	2016	WO	1	16	4
Barry Hawkins	3	2016	WO	0	16	4
Neil Robertson	**5**	2016	WO	1	16	2
Ding Junhui	2	2016	WO	0	16	2
Joe Perry	**5**	2016	WO	1	16	2
Ben Woollaston	1	2016	WO	0	16	2
Ronnie O'Sullivan	**5**	2016	WO	1	16	2
Mark Selby	1	2016	WO	0	16	2
Mark Allen	**5**	2016	WO	1	16	2
Michael White	0	2016	WO	0	16	2
Neil Robertson	**6**	2016	WO	1	16	1
Mark Allen	4	2016	WO	0	16	1
Ronnie O'Sullivan	**6**	2016	WO	1	16	1
Joe Perry	3	2016	WO	0	16	1
Ronnie O'Sullivan	**9**	2016	WO	1	16	0.5
Neil Robertson	5	2016	WO	0	16	0.5
Kyren Wilson	**13**	2016	WC	1	8	4
Mark Allen	9	2016	WC	0	8	4
Mark Williams	**13**	2016	WC	1	8	4
Michael Holt	8	2016	WC	0	8	4

Mark Selby	**13**	2016	WC	1	8	4
Sam Baird	11	2016	WC	0	8	4
Alan McManus	**13**	2016	WC	1	8	4
Ali Carter	11	2016	WC	0	8	4
Ding Junhui	**13**	2016	WC	1	8	4
Judd Trump	10	2016	WC	0	8	4
John Higgins	**13**	2016	WC	1	8	4
Ricky Walden	8	2016	WC	0	8	4
Barry Hawkins	**13**	2016	WC	1	8	4
Ronnie O'Sullivan	12	2016	WC	0	8	4
Marco Fu	**13**	2016	WC	1	8	4
Anthony McGill	9	2016	WC	0	8	4
Mark Selby	**13**	2016	WC	1	8	2
Kyren Wilson	8	2016	WC	0	8	2
Alan McManus	**13**	2016	WC	1	8	2
John Higgins	11	2016	WC	0	8	2
Ding Junhui	**13**	2016	WC	1	8	2
Mark Williams	3	2016	WC	0	8	2
Marco Fu	**13**	2016	WC	1	8	2
Barry Hawkins	11	2016	WC	0	8	2
Mark Selby	**17**	2016	WC	1	8	1
Marco Fu	15	2016	WC	0	8	1
Ding Junhui	**17**	2016	WC	1	8	1
Alan McManus	11	2016	WC	0	8	1
Mark Selby	**18**	2016	WC	1	8	0.5
Ding Junhui	14	2016	WC	0	8	0.5

Data for 2017

Name	round	year	match	win	H	C
Kyren Wilson	**5**	2017	CO	1	16	4
Stuart Bingham	2	2017	CO	0	16	4
Mark Williams	**5**	2017	CO	1	16	4
John Higgins	4	2017	CO	0	16	4
Hossein Vafaei	**5**	2017	CO	1	16	4
Rory McLeod	3	2017	CO	0	16	4
Judd Trump	**5**	2017	CO	1	16	4
Tian Pengfei	3	2017	CO	0	16	4
Mark Selby	**5**	2017	CO	1	16	4
Andrew Higginson	4	2017	CO	0	16	4
Shaun Murphy	**5**	2017	CO	1	16	4
Michael White	1	2017	CO	0	16	4
Stephen Maguire	**5**	2017	CO	1	16	4
Daniel Wells	1	2017	CO	0	16	4
Ding Junhui	**5**	2017	CO	1	16	4
Mark Joyce	3	2017	CO	0	16	4
Kyren Wilson	**5**	2017	CO	1	16	2

Ding Junhui	1	2017	CO	0	16	2
Mark Williams	**5**	2017	CO	1	16	2
Shaun Murphy	1	2017	CO	0	16	2
Hossein Vafaei	**5**	2017	CO	1	16	2
Judd Trump	3	2017	CO	0	16	2
Mark Selby	**5**	2017	CO	1	16	2
Stephen Maguire	1	2017	CO	0	16	2
Mark Selby	**6**	2017	CO	1	16	1
Kyren Wilson	4	2017	CO	0	16	1
Mark Williams	**6**	2017	CO	1	16	1
Hossein Vafaei	1	2017	CO	0	16	1
Mark Selby	**10**	2017	CO	1	16	0.5
Mark Williams	8	2017	CO	0	16	0.5
Mark Williams	**5**	2017	SM	1	8	4
Mark Selby	3	2017	SM	0	8	4
Judd Trump	**5**	2017	SM	1	8	4
Stephen Maguire	0	2017	SM	0	8	4
Ronnie O'Sullivan	**5**	2017	SM	1	8	4
Barry Hawkins	0	2017	SM	0	8	4
Kurt Maflin	**5**	2017	SM	1	8	4
Mei Xinwen	2	2017	SM	0	8	4
Jack Lisowski	**5**	2017	SM	1	8	4
Mark Allen	4	2017	SM	0	8	4
John Higgins	**5**	2017	SM	1	8	4
Liang Wenbo	2	2017	SM	0	8	4
Martin Gould	**5**	2017	SM	1	8	4
Marco Fu	2	2017	SM	0	8	4
Luca Brecel	**5**	2017	SM	1	8	4
Graeme Dott	4	2017	SM	0	8	4
Judd Trump	**5**	2017	SM	1	8	2
Luca Brecel	0	2017	SM	0	8	2
Ronnie O'Sullivan	**5**	2017	SM	1	8	2
Mark Williams	1	2017	SM	0	8	2
Jack Lisowski	**5**	2017	SM	1	8	2
Kurt Maflin	3	2017	SM	0	8	2
John Higgins	**5**	2017	SM	1	8	2
Martin Gould	1	2017	SM	0	8	2
Judd Trump	**6**	2017	SM	1	8	1
Jack Lisowski	3	2017	SM	0	8	1
Ronnie O'Sullivan	**6**	2017	SM	1	8	1
John Higgins	2	2017	SM	0	8	1
Ronnie O'Sullivan	**10**	2017	SM	1	8	0.5
Judd Trump	3	2017	SM	0	8	0.5
Joe Perry	**6**	2017	UK	1	8	4
Mark Allen	4	2017	UK	0	8	4
Ronnie O'Sullivan	**6**	2017	UK	1	8	4
Akani Songsermsawad	5	2017	UK	0	8	4

Shaun Murphy	**6**	2017	UK	1	8	4
Ricky Walden	1	2017	UK	0	8	4
Stephen Maguire	**6**	2017	UK	1	8	4
Graeme Dott	2	2017	UK	0	8	4
Mark King	**6**	2017	UK	1	8	4
John Higgins	5	2017	UK	0	8	4
Mark Joyce	**6**	2017	UK	1	8	4
Lyu Haotian	4	2017	UK	0	8	4
Martin Gould	**6**	2017	UK	1	8	4
Xiao Guodong	4	2017	UK	0	8	4
Ryan Day	**6**	2017	UK	1	8	4
Li Hang	5	2017	UK	0	8	4
Ronnie O'Sullivan	**6**	2017	UK	1	8	2
Martin Gould	3	2017	UK	0	8	2
Shaun Murphy	**6**	2017	UK	1	8	2
Mark King	1	2017	UK	0	8	2
Stephen Maguire	**6**	2017	UK	1	8	2
Joe Perry	3	2017	UK	0	8	2
Ryan Day	**6**	2017	UK	1	8	2
Mark Joyce	5	2017	UK	0	8	2
Ronnie O'Sullivan	**6**	2017	UK	1	8	1
Stephen Maguire	4	2017	UK	0	8	1
Shaun Murphy	**6**	2017	UK	1	8	1
Ryan Day	3	2017	UK	0	8	1
Ronnie O'Sullivan	**10**	2017	UK	1	8	0.5
Shaun Murphy	5	2017	UK	0	8	0.5
Zhou Yuelong	**4**	2017	WO	1	16	4
Lee Walker	0	2017	WO	0	16	4
Judd Trump	**4**	2017	WO	1	16	4
Hossein Vafaei	1	2017	WO	0	16	4
Robert Milkins	**4**	2017	WO	1	16	4
Mei Xinwen	2	2017	WO	0	16	4
Kurt Maflin	**4**	2017	WO	1	16	4
Yan Bingtao	1	2017	WO	0	16	4
Barry Hawkins	**4**	2017	WO	1	16	4
Craig Steadman	0	2017	WO	0	16	4
Scott Donaldson	**4**	2017	WO	1	16	4
Mark Davis	3	2017	WO	0	16	4
Stuart Carrington	**4**	2017	WO	1	16	4
Igor Figueiredo	1	2017	WO	0	16	4
Stuart Bingham	**4**	2017	WO	1	16	4
Robbie Williams	0	2017	WO	0	16	4
Judd Trump	**5**	2017	WO	1	16	2
Barry Hawkins	4	2017	WO	0	16	2
Robert Milkins	**5**	2017	WO	1	16	2
Kurt Maflin	2	2017	WO	0	16	2
Scott Donaldson	**5**	2017	WO	1	16	2
Zhou Yuelong	0	2017	WO	0	16	2

Stuart Bingham	**5**	2017	WO	1	16	2
Stuart Carrington	3	2017	WO	0	16	2
Judd Trump	**6**	2017	WO	1	16	1
Scott Donaldson	3	2017	WO	0	16	1
Stuart Bingham	**6**	2017	WO	1	16	1
Robert Milkins	0	2017	WO	0	16	1
Stuart Bingham	**9**	2017	WO	1	16	0.5
Judd Trump	8	2017	WO	0	16	0.5
Kyren Wilson	**13**	2017	WC	1	8	4
Stuart Bingham	10	2017	WC	0	8	4
Mark Selby	**13**	2017	WC	1	8	4
Xiao Guodong	6	2017	WC	0	8	4
Ronnie O'Sullivan	**13**	2017	WC	1	8	4
Shaun Murphy	7	2017	WC	0	8	4
Stephen Maguire	**13**	2017	WC	1	8	4
Rory McLeod	3	2017	WC	0	8	4
Ding Junhui	**13**	2017	WC	1	8	4
Liang Wenbo	12	2017	WC	0	8	4
John Higgins	**13**	2017	WC	1	8	4
Mark Allen	9	2017	WC	0	8	4
Barry Hawkins	**13**	2017	WC	1	8	4
Graeme Dott	6	2017	WC	0	8	4
Marco Fu	**13**	2017	WC	1	8	4
Neil Robertson	11	2017	WC	0	8	4
Mark Selby	**13**	2017	WC	1	8	2
Marco Fu	3	2017	WC	0	8	2
Ding Junhui	**13**	2017	WC	1	8	2
Ronnie O'Sullivan	10	2017	WC	0	8	2
John Higgins	**13**	2017	WC	1	8	2
Kyren Wilson	6	2017	WC	0	8	2
Barry Hawkins	**13**	2017	WC	1	8	2
Stephen Maguire	9	2017	WC	0	8	2
Mark Selby	**17**	2017	WC	1	8	1
Ding Junhui	15	2017	WC	0	8	1
John Higgins	**17**	2017	WC	1	8	1
Barry Hawkins	8	2017	WC	0	8	1
Mark Selby	**18**	2017	WC	1	8	0.5
John Higgins	15	2017	WC	0	8	0.5

Attachment 5: The comprehensive scores of snooker players

Name	init_R	RSM	R_{RSM}	add	PM	R_{PM}	CE	GOAT
Mark Selby	1994	2624	2	630	31.59%	2	1.6	1
Ronnie O'Sullivan	2198	2700	1	502	22.84%	5	2.4	2
Ding Junhui	2003	2584	3	581	29.01%	3	2.4	3
Stephen Maguire	2153	2509	4	356	16.54%	8	4.8	4
Neil Robertson	2121	2451	6	330	15.56%	9	6	5
Judd Trump	1975	2338	10	363	18.38%	7	6.8	6
Ali Carter	2105	2394	8	289	13.73%	10	7.2	7
Shaun Murphy	2183	2456	5	273	12.51%	13	7.2	8
Mark Williams	2161	2432	7	271	12.54%	12	7.6	9
Mark Allen	1637	2063	25	426	26.02%	4	11.6	10
Marco Fu	2047	2253	14	206	10.06%	15	11.6	11
John Higgins	2191	2373	9	182	8.31%	21	12	12
Stuart Bingham	2029	2225	16	196	9.66%	16	12.8	13
Barry Hawkins	2129	2305	11	176	8.27%	22	13.2	14
Ricky Walden	1918	2155	22	237	12.36%	14	14.4	15
Joe Perry	2081	2234	15	153	7.35%	25	16	16
Stephen Lee	2145	2291	13	146	6.81%	28	16.4	17
Peter Ebdon	2168	2291	12	123	5.67%	33	18	18
Anthony Hamilton	2097	2204	17	107	5.10%	37	21.6	19
Alan McManus	1747	1907	37	160	9.16%	18	22	20
Ben Woollaston	1878	1999	28	121	6.44%	30	23.2	21
Ryan Day	2089	2169	21	80	3.83%	39	24	22
Steve Davis	2137	2182	19	45	2.11%	46	26	23
Jamie Cope	1804	1904	38	100	5.54%	34	28.8	24
Gary Wilson	1584	1734	56	150	9.47%	17	29.2	25
Michael White	1724	1846	46	122	7.08%	27	29.2	26
Kurt Maflin	1938	1983	31	45	2.32%	44	30	27
Jack Lisowski	1878	1943	34	65	3.46%	41	30	28
Kyren Wilson	1000	1322	75	322	32.20%	1	30.4	29
Matthew Stevens	2113	2123	24	10	0.47%	55	31.6	30
Robert Milkins	1918	1948	32	30	1.56%	49	32.4	31
Joe Swail	1975	1988	29	13	0.66%	53	32.8	32
Stuart Pettman	1747	1840	47	93	5.32%	36	33.2	33
Dominic Dale	1888	1922	35	34	1.80%	48	33.2	34
Michael Holt	2029	2035	26	6	0.30%	57	33.2	35
Liang Wenbo	1570	1689	60	119	7.58%	24	33.6	36
Luca Brecel	1000	1226	79	226	22.60%	6	34	37
Anthony McGill	1793	1848	45	55	3.07%	42	34.8	38
A Higginson	1000	1136	81	136	13.60%	11	36.8	39
Hossein Vafaei	1468	1563	65	95	6.47%	29	37.6	40
Mark Davis	1804	1838	48	34	1.88%	47	38	41
Scott Donaldson	1205	1302	76	97	8.05%	23	39.6	42
Mike Dunn	1611	1672	61	61	3.79%	40	40.4	43
Jamie Jones	1804	1821	50	17	0.94%	51	40.4	44
N Saengkham	1000	1088	83	88	8.80%	19	40.8	45

Pankaj Advani	1452	1530	68	78	5.37%	35	41.2	46
Alfie Burden	1000	1085	84	85	8.50%	20	41.6	47
Martin Gould	1611	1659	62	48	2.98%	43	42	48
Mark Joyce	1688	1708	57	20	1.18%	50	42.8	49
Ken Doherty	2206	2182	18	-24	-1.09%	90	43.2	50
Joel Walker	1185	1260	78	75	6.33%	31	43.6	51
Jamie Burnett	1724	1735	55	11	0.64%	54	43.6	52
Marcus Campbell	1000	1071	85	71	7.10%	26	44.4	53
Stuart Carrington	1611	1622	64	11	0.68%	52	46.4	54
Graeme Dott	2176	2149	23	-27	-1.24%	93	46.4	55
Stephen Hendry	2213	2181	20	-32	-1.45%	96	46.4	56
David Grace	1000	1057	86	57	5.70%	32	47.2	57
Andy Hicks	1868	1861	42	-7	-0.37%	76	47.2	58
John Parrott	1857	1851	44	-6	-0.32%	75	47.6	59
Adrian Gunnell	1878	1870	41	-8	-0.43%	78	47.6	60
Matthew Selt	1836	1831	49	-5	-0.27%	71	48	61
Zhou Yuelong	1542	1549	67	7	0.45%	56	49.2	62
Jimmy White	1938	1919	36	-19	-0.98%	89	50	63
Ian McCulloch	2012	1986	30	-26	-1.29%	95	50	64
Nigel Bond	2064	2027	27	-37	-1.79%	98	50	65
Xiao Guodong	1000	1044	87	44	4.40%	38	50	66
Zhang Anda	1498	1497	70	-1	-0.07%	59	51.6	67
Liam Highfield	1556	1553	66	-3	-0.19%	65	52.4	68
Fergal O'Brien	1826	1816	51	-10	-0.55%	81	52.8	69
Mark King	1984	1946	33	-38	-1.92%	99	52.8	70
Peter Lines	1000	1023	88	23	2.30%	45	53.2	71
Oliver Lines	1527	1525	69	-2	-0.13%	64	53.2	72
Robbie Williams	1712	1705	58	-7	-0.41%	77	54	73
Dave Harold	1928	1894	39	-34	-1.76%	97	54.4	74
Daniel Wells	1483	1480	71	-3	-0.20%	69	56	75
Tom Ford	1938	1893	40	-45	-2.32%	101	56.4	76
Yu Delu	1804	1789	54	-15	-0.83%	88	56.8	77
Michael Wasley	1371	1368	73	-3	-0.22%	70	57.2	78
Barry Pinches	1700	1689	59	-11	-0.65%	84	57.2	79
Rory McLeod	1938	1860	43	-78	-4.02%	103	58.4	80
A Songsermsawad	1000	1000	89	0	0.00%	58	58.8	81
Rod Lawler	1663	1651	63	-12	-0.72%	86	59.6	82
Cao Yupeng	1000	999	90	-1	-0.10%	60	60	83
David Morris	1000	999	91	-1	-0.10%	61	60.8	84
Robin Hull	1468	1460	72	-8	-0.54%	80	60.8	85
David Gilbert	1847	1805	52	-42	-2.27%	100	60.8	86
Lu Ning	1000	999	92	-1	-0.10%	62	61.6	87
Michael Judge	1847	1794	53	-53	-2.87%	102	62	88
Michael Georgiou	1000	999	93	-1	-0.10%	63	62.4	89
James Cahill	1000	998	94	-2	-0.20%	66	64	90
Jamie O'Neill	1122	1117	82	-5	-0.45%	79	64.4	91
Sam Baird	1371	1361	74	-10	-0.73%	87	64.4	92
Li Hang	1000	998	95	-2	-0.20%	67	64.8	93

Zhao Xintong	1000	998	96	-2	-0.20%	68	65.6	94
Lyu Haotian	1000	997	97	-3	-0.30%	72	67.6	95
Martin O'Donnell	1000	997	98	-3	-0.30%	73	68.4	96
Craig Steadman	1318	1301	77	-17	-1.29%	94	68.4	97
D Poomjaeng	1225	1210	80	-15	-1.22%	92	68.8	98
Yan Bingtao	1000	997	99	-3	-0.30%	74	69.2	99
Igor Figueiredo	1000	994	100	-6	-0.60%	82	72.8	100
Mei Xinwen	1000	994	101	-6	-0.60%	83	73.6	101
Lee Walker	1000	993	102	-7	-0.70%	85	74.8	102
Tian Pengfei	1000	989	103	-11	-1.10%	91	77.6	103

Attachment 6: Notations

Symbol	Description
R_A	Player A's ranking score
E_A	Player A's expectation of winning
$\overline{R_A}$	Ranking score of player A after the competition
H	Weight of competition level
W	The result of the competition
seed	Seed ranking of woman tennis players
χ_{PR}	Indicator function of players' PR status
P	Game performance of players
Δ_i	The score difference in the i-th game
C_k	The weight of the round
P_A	Player A's score in the progress model (PM)
R_{RSM}	Player's ranking in RSM
R_{PM}	Player's ranking in PM
R_A^0	Initial score of player A in RSM
CE	Player's comprehensive score in CEM
λ	Weight coefficient in CEM
S	Player's out state
$Rank_0$	Initial world rankings of snooker players
l_i	The number of winning games required for the i-th round
$P_{n,k}$	In n games, the probability of a player winning k games

Attachment 7: Model Evaluation

Some assumptions and default parameters of the model may contain errors. For example, we assume that the expectation of winning follows a normal distribution (but in the Elo algorithm, the statistical characteristics indicate that the chess player's expectation of winning is more in line with the Logistic distribution).

Considering the establishment process of the G.O.A.T. model and the meaning of each parameter in the model, our model has the following advantages:

- Based on the Elo algorithm, it considers the expectation of winning in confrontation, instead of just updating the ranking score based on the result of winning or losing. The extra points (or deductions) will be evaluated based on the current strength of both parties to ensure the fairness of the algorithm.
- The update of the ranking score will consider factors such as the level of the game, the round of the game, the performance of the game, and the state of the player. In particular, the setting of game performance P is the core of the reward and punishment mechanism that enhances the update of ranking scores.
- The criterion of "the greatest" is not only to consider the accumulation of the players' achievements, but to pay more attention to whether the players achieve "self-breakthrough". The combination of the RSM and the PM makes the comprehensive evaluation indicators more objective and fairer, and more in line with our definition of "the greatest".
- The principle of our model is simple and easy to implement, and can be easily extended to any movement. For any individual sport, the G.O.A.T. model only needs to change the definition of the initial ranking score and game performance.

Regarding the update of the ranking score, the model only considers the update of the scores of both parties when the two players are playing. In fact, the strength relationship of all players in the same sport should form a network structure. The result of any game will affect the strength relationship between players derived from the network structure (for example, player A can defeat player B, player B can beat player C, and player C can beat player A, the relationship between the strengths of the three will form a circular network). We believe that using the network structure to consider the update of the ranking scores will enrich the algorithm, but it will also make the work difficult and cumbersome.

Finally, we propose another way to define the game performance P. In fact, when we calculate the expectation of winning E_A, for a round of n rounds in which a total of n rounds are played, the probability $P_{n.k}$ that player A will win k games is:

$$P_{n,k} = \Pr\left(A \text{ won } k \text{ games}\right) = \binom{n}{k} \cdot \left(E_A\right)^k \cdot \left(1 - E_A\right)^{n-k}$$

Player A's expectation for winning games is $E_A^n = n \cdot E_A$. Therefore, we can define the game performance of A on the basis of E_A^n. E_A^n is the number of times A should win in each round. When the number of wins of A is greater than E_A^n, we can let the game performance P becomes the incentive item for the ranking score update; and when A's wins are less than E_A^n, let the game performance P be the penalty item for the ranking score update.

Attachment 8: Main code of G.O.A.T model (Python)

```python
import pandas as pd
Snooker = pd.read_excel('Snooker2007.xlsx')
player = pd.read_excel('Snooker_player2007.xlsx')
player['init_rank'] = 1000
for i in range(len(player)):
    if type(player['rank'][i]) == int:
        player.loc[i,'init_rank'] = 1000 + round(10**3*np.log(4*(94-player.loc[i,'rank']/2)-100)-4400)
player['new_rank'] = player['init_rank']
Snooker['P'] = 0
Snooker['E'] = 0
for i in range(int(len(Snooker)/2)):
    n1 = Snooker.loc[2*i,'Name']
    n2 = Snooker.loc[2*i+1,'Name']
    r1 = Snooker.loc[2*i,'round']
    r2 = Snooker.loc[2*i+1,'round']
    w1 = Snooker.loc[2*i,'win']
    w2 = Snooker.loc[2*i+1,'win']
    delta = np.abs(r1-r2)
    l = max(r1,r2)
    N = np.sqrt(l) - 1
    p1 = 0.5 + 1/(1+np.exp((-1)**w1*delta/N))
    p2 = 0.5 + 1/(1+np.exp((-1)**w2*delta/N))
    Snooker.loc[2*i,'P'] = p1
    Snooker.loc[2*i+1,'P'] = p2
    rank1 = int(player.loc[player.loc[:,'Name']==n1,'new_rank'])
    rank2 = int(player.loc[player.loc[:,'Name']==n2,'new_rank'])
    E1 = 1/(1+np.exp((rank2-rank1)/400))
    E2 = 1 - E1
    Snooker.loc[2*i,'E'] = E1
    Snooker.loc[2*i+1,'E'] = E2
    add1 = p1*Snooker.loc[2*i,'H']*Snooker.loc[2*i,'C']*(w1-E1)
    add2 = p2*Snooker.loc[2*i+1,'H']*Snooker.loc[2*i+1,'C']*(w2-E2)
    player.loc[player.loc[:,'Name']==n1,'new_rank'] += round(add1)
    player.loc[player.loc[:,'Name']==n2,'new_rank'] += round(add2)
player.to_excel('Snooker_player2007_result.xlsx')
```