WHO IS THE GREATEST?

IMMC US-10656

1. Executive Summary

The discussion around sports is in many ways a direct reflection of their competitive nature, with constant debate and discussion regarding the "G.O.A.T." - the undisputed premier athlete - for every sport which has been constructed. For practically any given sport, there exist multiple candidates who could be considered the greatest according to diverse criteria, representative of the many intricacies of different sports. In this paper, we develop several models of specific sports able to pinpoint an objective G.O.A.T. based on performance results alone. We extend and adapt our models, developed in detail for women's singles tennis and speedcubing, to generalized individual sports as well as team sports.

Our first model created a rating system, taking each of the 189 participants and 508 total matches in the 2018 Grand Slam tournaments for women's singles tennis into account. Specifically, for each matchup, the model updated a Greatness Score based on previous ratings, the scores of the match, and the importance of the round they were playing in. We then inputted the list of matches into the model 1000 times, shuffling each time to determine the final greatness. Based on our model, Simona Halep was determined to be the G.O.A.T. of 2018 Women's Tennis.

Our second model evaluated the performance of competitors in 3x3x3 speedcubing, a sport with an inanimate standard, over the entirety of the its formal existence. We gathered data from the finals round of every tournament recorded in the careers of 36 notable cubers, before deriving a formula to compare each cuber with their competitors by year in the form of an initial Greatness Score. We implemented a function that accounts for decline in a cuber's ability, with additional considerations from world record solves. Our model determined the G.O.A.T. of 3x3x3 speedcubing to be Feliks Zemdegs.

The two models can be easily translated to similar individual sports of their nature. Singles tennis and speedcubing are matchup-dependent and standard-dependent respectively. All individual sports can be classified into these two categories, and as such, the aspects of both models can be translated across to sports such as boxing or swimming.

However, these two models also form excellent complements to each other, and can be integrated together to develop a model for team sports. The two models are components of the factors of individual and team performance, and with adjustments made for individual player value, this new derivation of our original models can determine the G.O.A.T. of any team sport. In this way, our models are able to be easily adapted to fit the great diversity of the sporting world.

In a letter to the Director of Top Sport, we offered brief and easily understandable, yet in-depth summaries of how our models function and their key findings, as well as explanations of our models' versatility and applicability to the universal world of sports.

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2. Introduction

Over the millennia of its existence, human civilization has come to innovate and develop a myriad of competitive recreational activities, broadly grouped and defined as "sports". As an inquisitive species, we are naturally inclined to determine which individual among us is the greatest competitor of any given sport. In the quest for the answer, we collect statistics about the performance of athletes and teams, throw our sympathies behind our favorite competitors, and fiercely debate with each other, in hopes to discover who is truly the greatest of all time.

There is seldom an undisputed greatest-of-all-time for any given sport, with different criteria pointing to various individuals over the course of history and the present. With a diverse array of tremendously intricate sports with rich histories of greatness available to us, how can it be possible to ascertain the objectively absolute best individual? Which factors should be considered, and which are most important? How can a model for greatness be adapted across different sports and eras?

3. Women's Singles Tennis, 2018

Women's singles tennis is an individual sport in which two opponents play against one another with the objective of winning two sets. Although the format varies by tournament, a set is typically won after winning at least seven games by a margin of at least two games, or winning a special tiebreak with at least seven points by a margin of at least two points.

In our first model, we determined the greatest women's singles tennis player in 2018, based on performance at the Australian Open, French Open, Wimbledon Championships, and U.S. Open for that year. [10] [8] [9] [7] For each of these four tournaments, 128 players were seeded according to rankings held by the Women's Tennis Association (WTA) and qualification tournaments, and played in a single-elimination bracket to decide the winner.

3.1. **Assumptions.**

(1) **Assumption:** A tennis player's greatness is not influenced by variables unrelated to their tennis performance.
Justification: We assumed that matchup (relative strength of opponents) and match results alone contribute to one's greatness, which is not affected by off-the-court variables. It is difficult to take into account factors such as character, popular support, or legacy for the large number of unique individuals participating in these tournaments. Additionally, there does not exist a method to quantify these highly subjective variables.

(2) **Assumption:** All tennis matches were played with intentions to win. No factors contributed to matchup competitiveness or match results besides skill in tennis.
Justification: Relationships between opponents or other match details are too nuanced to yield a decisive effect on the greatness of a player. There are many examples of these: opponents from the same country, opponents related familially, players playing in their home country, and rivalries between opponents.

(3) **Assumption:** Performance in the 2018 Australian Open, French Open, Wimbledon, and U.S. Open tournaments determined a tennis player's greatness in 2018 equally. No other tournaments contributed to greatness.

Justification: These four tournaments, collectively known as the Grand Slam tournaments, generally involve the best players in the world. Due to the high-profile prestige of these tournaments, as well as the strength of the playing field, we assumed that these tournaments alone would evaluate a player's greatness. The four are weighted with equal importance, as WTA rating points are awarded in equal amounts at each. [6]

(4) **Assumption:** The pressure to win a tennis match increases based on how far into a tournament the match occurs.
Justification: As a tournament advances, more WTA rating points are at stake. Also, the potential for winning the tournament or placing highly for a given player, regardless of skill, increases dramatically. The matchup competitiveness naturally increases due to weaker players being eliminated in earlier rounds.

3.2. **Variables.**

The most important variable in this model is the **greatness score**, denoted by g. First, each player is assigned an initial greatness score of $g = 0$. The model works by simulating all matches in the four Grand Slam tournaments and updating the greatness scores of players after each match. This is run for 1000 iterations (each tournament is simulated for 100 rounds), until a clear ranking of greatness scores is established, at which point the G.O.A.T. is easily identifiable.

Each match in the simulation updates the greatness scores of the winner and the loser according to the **update variables**, denoted by u_1 and u_2, respectively. The update variables are determined by the following variables corresponding to each match:

(1) **Competitiveness (m)**: Every matchup in a tournament has a competitiveness level, which is determined by how close the greatness scores of the players are at the instant before the match. If the greatness scores are close, the match is competitive and could swing either way, resulting in a competitiveness score that is low in magnitude. If the greatness scores are farther apart, the match is less competitive and the competitiveness score is higher in magnitude. Very competitive matches do not greatly affect greatness scores, and neither do non-competitive matches that have the expected outcome. However, if the underdog comes out on top in a non-competitive matchup, the underdog's greatness score will go up more significantly and the favorite's greatness score will go down more significantly.

(2) **Round Importance (R_i)** For $1 \leq i \leq 7$, R_i is the importance of round i of the tournament (there are seven rounds in a Grand Slam from the first round to the final). The G.O.A.T. should be able to perform well in high-pressure situations, and should be able to play well in later rounds of the tournament, as these are the rounds that people remember the most. These variables help the model account for later rounds of the tournament being more important, so that wins in these rounds are factored more heavily in the greatness score than wins in the earlier rounds. However, losses in these rounds are factored less heavily than losses in the earlier rounds, as being knocked out of the Grand Slam late in the tournament does not affect greatness as

much as being knocked out of the tournament early on.

(3) **Domination Score (d)**: The G.O.A.T. should be able to win decisive victories, dominating their opponents on the field. The domination score quantifies how dominant the winning player was on the field.

In order to calculate the domination score (entry 2 in the above list), we must calculate a few auxiliary variables, which are also unique to each match:

(1) **Domination Sum (s)**: While calculating the domination score, we keep track of a domination sum, which is modified after every set of a match depending on which player won that set and how decisively they won it.

(2) **Tie Factor (T_i)**: For $1 \leq i \leq 3$, t_i is the tie factor of set i. If a set results in a 6-6 tie, it moves to tiebreakers. If this is the case, the tie factor T_i for that set is calculated based on how competitive the tiebreaker game was. The domination sum is then modified accordingly.

Each match also has a few variables that come directly from the data. In what follows and for the rest of the paper, we refer to the winner of the match as the first player:

(1) For $1 \leq i \leq 3$, L_i is 1 if the first player won the ith set of the match and 0 otherwise. Note that L_3 does not exist if a match was won in two sets. One can think of this as a boolean variable that is true if the first player won the ith set and false otherwise.

(2) For $1 \leq i \leq 3$, s_{1i} is the number of games the first player won in the ith set. Once again, s_{13} does not exist if the match was won in two sets. Similarly, s_{2i} is the number of games the second player won in the ith set.

(3) For $1 \leq i \leq 3$. t_{1i} is the number of points the first player won in the tiebreaker after the ith set, if it exists. The three variables $t_{2i}, 1 \leq i \leq 3$ are defined similarly.

3.3. **Development of Model.**

First, the data given in the problem, which only included results from the fourth round onwards in all four Grand Slams, was extended to include results from all rounds in each of the tournaments. This was done by manually inputting data from Wikipedia into a spreadsheet which could then be inserted into a program. Collecting results from all rounds of every tournament allowed for more comprehensive data to be used in determining the G.O.A.T., especially since several serious contenders for the title did not make the Fourth Round in some of the tournaments.

As briefly elaborated on in the variables section, the model, on a high level, works by first assigning each player an initial greatness score $g = 0$. Then, each Grand Slam is simulated, with each player's greatness score being updated after every match they play. This is run for

1000 iterations with the match list shuffled between each iteration until a clear ranking is established. This ranking is the final ranking of Women's Singles players in 2018, by greatness.

There are three factors that determine how the greatness scores are changed for each match: the domination score, the round importance, and the competitiveness. The domination score scores how decisively a player played in a match. To calculate the domination score d, we must first calculate the domination sum s. This is calculated using the following equation:

$$s = \sum_{i=1}^{3} (-1)^{L_i+1} (0.8)^{s_{1i}+s_{2i}-6} T_i$$

To see how this equation works, consider the ith set. If $L_i = 1$ (the first player won the set), the domination sum is increased, and the domination sum is decreased if $L_i = 1$. Since the first player won the match, the domination sum will be increased exactly twice throughout the match. Next, note that $s_{1i} + 2_{2i} - 6 \geq 0$ since at least 6 games are played in every set. The more games are played, the less dominant the winner of that set was, so the less the domination sum is modified (since 0.8 will have a higher exponent if more games are played). The last component is the tie factor T_i, which is 1 if no tiebreaker is played, and thus has no effect on the domination sum unless a tiebreaker is played. If a tiebreaker is played, we use the following equation to calculate the tie factor:

$$T_i = \frac{5}{4} (0.9889)^{\min((t_{1i}+t_{2i}-7),20)}$$

This functions similarly to the $(0.8)^{s_{1i}+s_{2i}-6}$ term, which multiplies by 0.8 for each game played over the most dominant case (6-0). The more points are scored in the tiebreaker (which is measured by $t_{1i} + t_{2i}$), the less dominant it was, which corresponds to the exponential decay term decreasing with a larger exponent. The exponent caps at 20 so that the tie factor does not affect the domination sum any more than a normal game in a set. This is why the constant 0.9889 was chosen, since $\sqrt[20]{0.8} \approx 0.9889$. The $\frac{5}{4}$ multiplier is to make sure the tiebreaker game is not overcounted, since it is counted in the total number of games as well. By dividing by 0.8, we ensure it is only accounted for inside the tie factor.

After calculating these, we calculate the final domination score for that match with the following equation:

$$d = 1.5 - \left(\frac{1.5}{1 - (0.3)^3} \right) (1 - (0.3))^{2-s}$$

The domination sum is always in the closed interval $[-1, 2]$ since the domination sum is changed by at most 1 at each step, and it must increase exactly twice throughout the match (and may decrease once). Thus, $1 - (0.3)^{2-s}$ is in the interval $[1 - (0.3)^3, 1]$, which puts the whole sum in the range $[0, 1.5]$. The closer s is to 2, the higher the domination sum is. Exponential growth was chosen so that sums closer to 2 were rewarded more than sums closer to -1 were penalized. The constant 0.3 was chosen experimentally.

The next factor is m, the competitiveness of the match, which is calculated as

$$m = \frac{g_1 - g_2}{50}$$

This equation measures the competitiveness of the match by simply taking the positive difference of the two players' greatness scores. The bigger this difference, the less competitive the match was. This difference is then divided by 50 for scaling, so it does not affect the update too much.

The last factor is R_i the round importance. The round constants are defined by $R_i = (1.2)^i$, where i measures the round of the competition minus 1 (so the first round is 0). This makes it so that later rounds are exponentially more important than earlier rounds, greatly increasing their value.

After the domination sum is calculated for the match, the players' ranks can be updated. The winner's rank is updated by u_1 and the loser's by u_2 as described by the equations below:

$$u_1 = 5\left(1 - \frac{1}{1+5^{-m}}\right)\frac{1}{d}R_r$$

$$u_2 = -5\left(\frac{1}{1+5^{m}}\right)\frac{1}{d}\frac{1}{R_r}$$

These update variables are added to the respective player's greatness scores before the match, so the first player (the winner) has their greatness score increased and the second player (the loser) has their greatness score decreased. We use a logistic model on the match competitiveness to adjust the scores appropriately. This way, if favorite beats the underdog, the favorite will gain less points and the underdog will lose less points while if the underdog beats the favorite, the favorite will lose more points and the underdog will gain more points. The more mismatched their greatness scores are, the higher the disparity in the points lost and gained when comparing the favorite and the underdog.

Note that the logistic model is multiplied by the round constant for the winner's update and is divided by the round constant for the loser's update. This makes it so that winning a late match helps the winner a lot and hurts the loser less while winning an earlier match helps the winner less and hurts the loser more. Finally, the logistic model is multiplied by $\frac{1}{d}$ for both updates so that more dominant matches help the winner more and hurt the loser more while less dominant matches help the winner less and hurt the loser less.

Lastly, the ratings are multiplied by

$$0.8^{max(0,3-t)}$$

where t is the number of tournaments attended by a player. This is factored in because a more active player should have a better chance of being the G.O.A.T, and a player who missed tournaments should receive a penalty.

These equations are used for each match to continually update the greatness scores of all players, which eventually results in a definitive ranking after each tournament is simulated many times (in practice, 1000 times). The greatness scores are scaled linearly so that the top player has a greatness score of 100 and the lowest player has a greatness score of 0.

3.4. **Results and Discussion.**

The results showed that the greatest women's singles tennis player in 2018, as determined by their Grand Slam tournament results, was Simona Halep of Romania, with a scaled greatness score $g = 100.000$. The model is clearly justified in this decision, as Halep ranked as world 1 for virtually the entirety of 2018, won the French Open, and was decided Player of the Year by the Women's Tennis Association.

Notably, the model placed the four unique winners of the Grand Slam tournaments in the top four positions: Angelique Kerber, winner of the Wimbledon Championships, in second ($g = 99.411$); Naomi Osaka, winner of the U.S. Open, in third ($g = 98.880$); and Caroline Wozniacki, winner of the Australian Open, in fourth ($g = 98.394$).

The results did present several extremely interesting cases. Serena Williams, who missed the Australian Open due to the recent birth of her child, fell right behind the winners of the Grand Slam tournaments due to her excellent performances in matches for the rest of the year ($g = 97.850$). Deemed the Comeback Player of the Year by the WTA, she was the only athlete out of the top 25 tournament competitors to miss a Grand Slam tournament, reflective of her strong performance and greatness.

Further down the list, Vitalia Diatchenko ranked 70th ($g = 63.297$) despite only participating as a qualifier in the Wimbledon Championships. How is this possible? If we examine her opponents, we can see that she emerged victorious over 10th-ranked Maria Sharapova and 34th-ranked Sofia Kenin, the latter of which she beat in two sets. Having this singular run of greatness in just one tournament both elevates her to well above average for a relative unknown to the Grand Slam tournaments, but still restricts her to an appropriate greatness score as determined by the model.

On the opposite end of the spectrum, we find Polona Hercog, who is ranked 187th out of 189 total players ($g = 2.415$). She lost in straight sets in 3 out of 4 tournaments, often beaten by players ranked as below-average by the model. This explains why her greatness score is continuously pushed downwards, despite her having won more total games compared to players like Diatchenko.

Figures 1 and 2 show the top 24 and 25th to 75th ranked Women's Singles tennins players, respectively.

3.5. **Additional Analysis of the Model.**

When trying to incorporate seeds into the initial values of each player's ratings we found almost no change in the results at all. Even randomizing the initial values to be between -1000 and 1000 gave final greatness scores to have differences almost exactly the same as the original. This shows that the model is completely based on the games played that year, and the initial ratings of players will have essentially no effect on the final result.

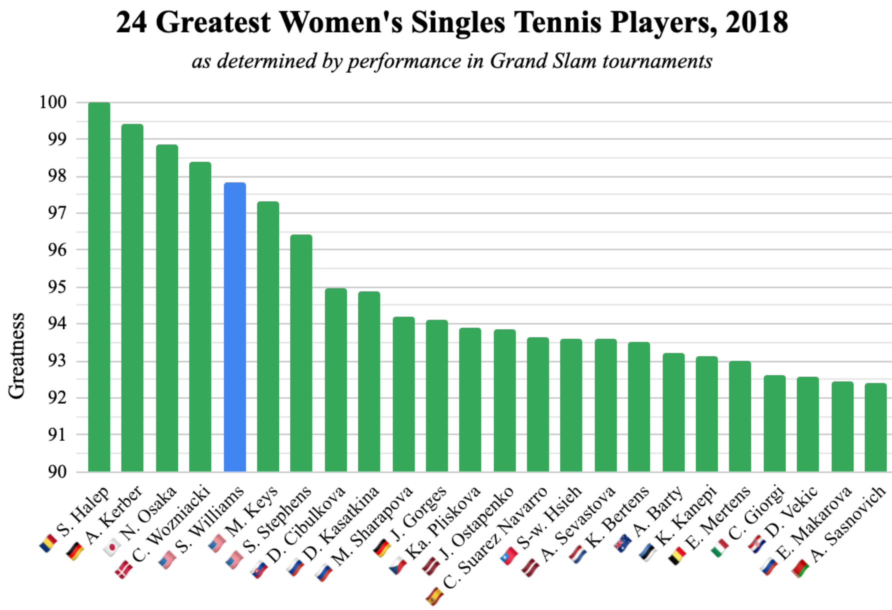

Figure 1. The top 24 players had greatness score ranges from 100.000 to 92.422. Green represents players who participated in four Grand Slam tournaments. Blue represents players who participated in three.

4. Speedcubing

4.1. **Assumptions.**

(1) **Assumption:** A cuber's greatness is not influenced by variables unrelated to their performance.

Justification: A cuber's performance should be restricted to their solving times only. There is far too much data to consider if, for example, individual moments that sparked popularity were considered. Additionally, greatness determined from popularity factors is largely subjective, and very difficult to model mathematically. It is difficult to take into account factors such as character or legacy which may influence the perception of a cuber's greatness. Additionally, there does not exist a method to quantify these variables. For the initial model, these factors cannot be considered.

(2) **Assumption:** A cuber's performance is not influenced by variances in the competition environment.

Justification: It is impossible to gauge the influence of such external variables on solving times. With cubing, there are many such details which vary drastically

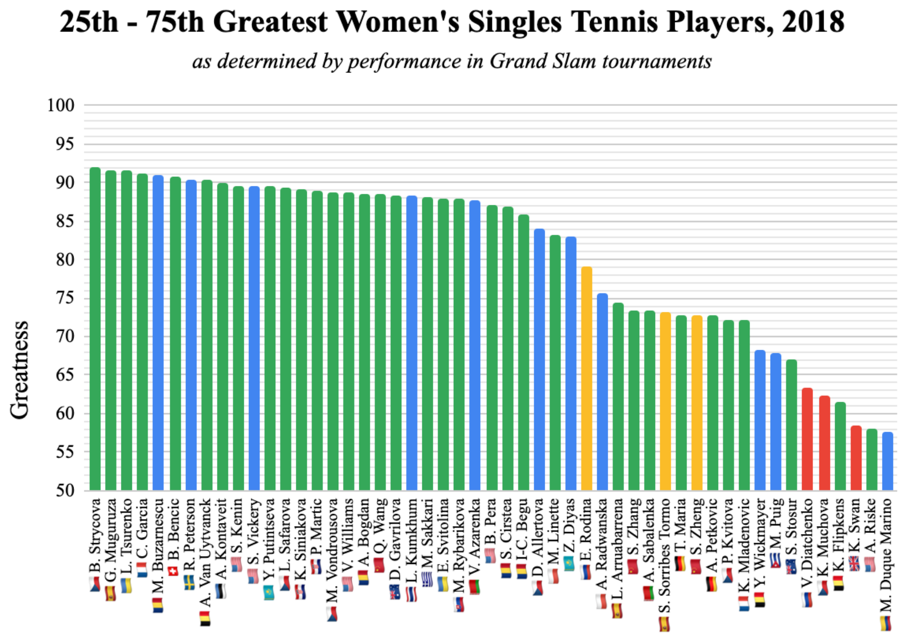

FIGURE 2. The next 50 players had greatness score ranges from 91.959 to 57.730. Green represents players who participated in four Grand Slam tournaments. Blue represents players who participated in three, yellow for two, red for one.

based on the tournament. Location, amount of spectators, procedures such as method of timing and cube concealing, time given for cube inspection, strength of playing field, results in previous rounds, and initial cube scrambles are assumed to have no significant effect on a cuber's performance. Moreover, many of these variances are extremely subtle and are essentially standardized.

(3) **Assumption:** The evaluation of cubing greatness begins in 2003, and continues to the present day. All competition results are taken from the World Cube Association's player database. [3]

Justification: The first documented cubing competitions occurred in 1982. However, the World Cube Association, the central regulating body of cubing competitions, held their first world championship in 2003, when competitions began to occur more regularly and grow in popularity [1]. Thus, we assumed 2003 to be the first year in which the results of cubers are eligible for analysis. Because we considered the greatest of all time, we included results leading up to the present day, but not projected results.

(4) **Assumption:** For all cubers, only the final rounds of competitions are considered. Furthermore, each time of competition is simplified to the year of its occurrence.

Justification: Since 2003, all final rounds of WCA competitions have used a regulated method of calculating scores: each cuber solves 5 Rubik's cubes, their fastest and slowest times are taken out, and the remaining three are averaged. Furthermore, the final rounds of tournaments exert a level of pressure from spectators and strong playing fields which is necessary to determine the greatest cuber of all time [4]. Although the WCA records the specific dates of competitions, the competitions are easily organized by year in the interest of constructing an effective model. Unlike women's singles tennis, the top cubers do not all participate in the same tournaments, which necessitated this assumption.

4.2. Variables.

The **Greatness Score** (g_c) for person c is determined by how well a person performs in competition and their world records. The following variables help in determining the competition score:

(1) **Average Time For Person c In Year i ($\mu_{c,i}$)** The average solving time for person c in year i is denoted by $\mu_{c,i}$. This is the average of all their final round averages throughout year i of competition.
(2) **Set of Average Times For Person c (μ_c** The set of average times for person c across all years active is denoted by μ_c. In other words, $\mu_c = \{\mu_{c,i}|$ person c competed in year $i\}$.
(3) **Yearly Competition Score ($\omega_{c,i}$)** This is the competition score of person c in year i. This is based on the person's competition times with respect to everyone else's times that year.
(4) **Competition Score (ω_c)** This is the competition score of person c over all years. It is the weighted average of all $\omega_{c,i}$.
(5) **People Active (p_i)** This is the number of top level people active in year i.
(6) **Yearly Z-Score ($Z_{c,i}$)** This is the z-score of $\mu_{c,i}$ over all averages for people in year i.

The following variables help in determining the record score:

(1) **Record Score (R_c)** This measures how significantly person c has contributed to world records.
(2) **Record value (v)** This measures the value of a single record.
(3) **Record Improvement (r)** This is the ratio of the new record over the previous record.
(4) **Record Duration (t)** This is the time for which the record was held in days.

4.3. Development of Model.

The first step was to comb the set of cubers to just a set that would be feasible to be all-time G.O.A.Ts of the sport, in order to keep the data manageable. As stated in the assumptions, we only work with the years 2003 and after. By examining world record holders and frequent appearers in the WCA World Championships, we selected a set of 36 cubers who competed from 2003 onwards, all of whom had a decent shot at being named the G.O.A.T.

Then, we collected the raw data for the model. Even with just 36 cubers, it would be too much to record all solve times from all rounds of all competitions they have participated in. Thus, for each competition one of the competitors reached the finals in, the average solve time and year was required. Only the finals were collected since they are high-stakes events and the finals are very standardized: the average of 5 3x3x3 solves are taken for the final average solve time in the finals of that tournament.

After all the data from final rounds was gathered, it was compressed several times. Each final round for each competitor consists of 5 separate solves, which were all averaged to get one number for each competitor's final round in each year. Then, all averages for a competitor were averaged to get a single number to represent each competitor in each year. As stated in the variables section, this average time in year i for person c is $\mu_{c,i}$. In addition to the set of μ variables, we keep track of p_i for each year i, the number of competitors competing in year i.

After this, we calculate the competition score for each person in each year:

$$\omega_{c,i} = Z_{c,i} \log(p_i)$$

This is the competition score for person c in year i, where p_i is as described above and $Z_{c,i}$ is the z-score of $\mu_{c,i}$ with respect to the set μ_i. The z-score measures how far above or below person c is compared to the average time in year i, enabling us to determine how that person is doing compared to the average of their year. Multiplying by $\log(p_i)$ takes into account the fact that some years are more competitive than others, so being above the mean in a more competitive year is worth more than being above the mean in a less competitive year.

A higher ω score in a certain year corresponds to that player being better in comparison to the rest of the players in that year. When determining the G.O.A.T., we want to take into acount the standards of the time they were competing, which is why we use ω scores as our initial measurement of greatness.

It then remains to combine the ω scores for a single person over the years of their career. This is done through a weighted average. Specifically, the peak year of person c's career is found by taking the year i with the maximum $\omega_{c,i}$ for that person. Then, all $\omega_{c,j}$ scores for person c are summed, with a year j weighted with a weight of $e^{-\frac{|j-i|^2}{100}}$, a normal distribution based on the number of years away from the peak. This makes it so that years close to the peak are weighted heavily and years farther from the peak are weighted less heavily. A weighted average of all $\omega_{c,j}$ scores is taken with those weights to get an overall ω_c score for that person.

Then, the world records are taken into account. We define the value, v, of a certain record to be

$$v = \frac{t}{5 \cdot 365}\left(\frac{1}{r}(1 + 0.01 \cdot p_i) - 1\right)$$

We use $\frac{1}{r}$ since the lower the ratio of the new record over the previous record, the higher we want the value to be. We also add in the $(1 + 0.01 \cdot p_i)$ factor since when more people participate, it is harder to hold world records and record holders get more attention. Both these factors generally give values slightly above 1, so subtracting 1, we get a small value above 0. Lastly, we multiply by a factor of $\frac{t}{5 \cdot 365}$ to signify that records held for longer are worth more. The constant of $\frac{1}{5}$ was chosen experimentally to match our desired effect of the value. The value generally is a small number above 0.

Next, we define the the record factor of a person to be

$$R_c = 1 + \sum v$$

summing over all records held by person c.

Finally, we calculate the greatness scores of each person to be

$$g_c = w_c R_c$$

combining their competition score and record factor. The scores were then scaled linearly so that the highest score scaled to 100 and the lowest score scaled to 0.

4.4. **Results and Discussion.**

The results showed that the G.O.A.T. of 3 by 3 by 3 Speedcubing, as determined by their competition times and records, is Felix Zemdegs of Australia by a large margin, with a scaled greatness score $g = 100.000$. Max Park, the second greatest is far behind with a greatness score of $g = 61.268$. The model is clearly justified in this decision, as Zemdegs has repeatedly gets dominating times in competition over many years, he has held 23 records overall in average times and single times, and is often considered to be the greatest Speedcuber in the Speedcubing community.

The results also show the trends with how the time a player peaked affected their greatness score. In general, players who peaked later had a higher greatness score. This makes sense as more people were involved in Speedcubing over time, and in our model, we placed more importance on accomplishments when the sport was more popular.

Figures 3 and 4 show the top 15 and 16th to 36th ranked 3x3 speedcubers, respectively.

4.5. **Additional Analysis of the Model.**

If we disregard world records, we found that Zemdegs was still in the lead, however his lead was much less dominating with Max Park scoring 86.224. This shows that the records helped boost Zemdegs' score greatly in comparison to other competitors.

5. Adaptations for Individual Sports

As we desire to adapt our model for any individual sport, we begin with the consideration of all of the different types of individual sports. We rigidly define the categorical distinctions for individual sports as being physical versus non-physical and one-on-one versus with an inanimate standard, thus creating a total of 4 possible categories for any individual sport, shown in Figure 5. They are:

- Physical individual sport with an inanimate standard
- Nonphysical Individual Sport with an Inanimate Standard
- Physical One-on-One Individual Sport
- Nonphysical One-on-One Individual Sport

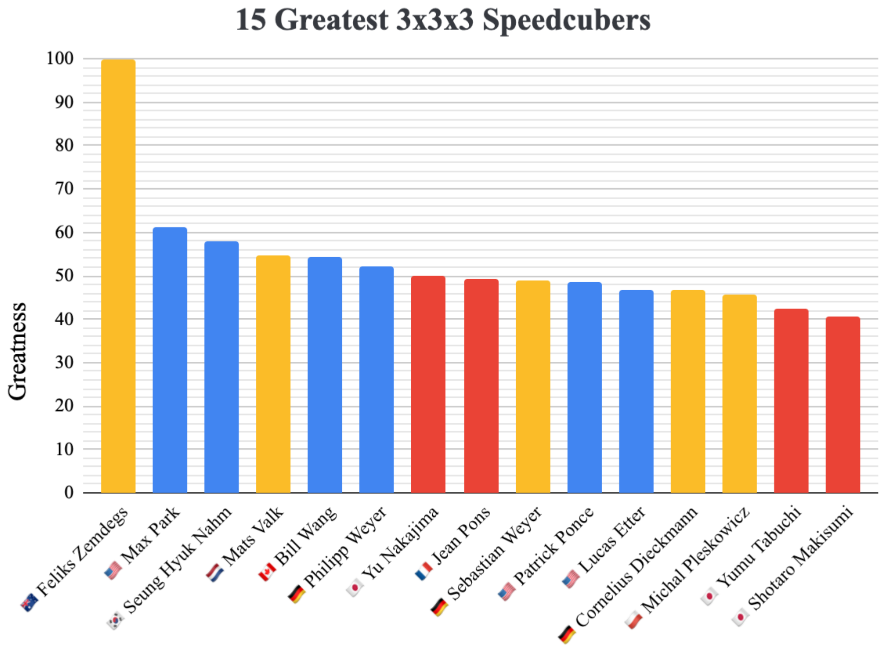

FIGURE 3. The top 15 players had greatness score ranges from 100.000 to 92.422 to 40.594. Red represents peak years 2003-2009, yellow represents peak years 2010-2015, and blue represents players with peak years 2016-2021.

5.1. Adaptations for Individual Sports with an Inanimate Standard.

Similar to our model for Speedcubing, the model for any individual sport must first determine a pool of competitors that are in contention for G.O.A.T. status. As Speedcubing is a very new sport, our best method of narrowing down this candidate list was looking at World Championship appearances and world records. For sports with longer histories and establishments (such as Halls of Fame, All-Stars, etc.), there are more options available for determining potential greats. In order of importance, our proposed criteria for narrowing down competitors goes as follows:

(1) **Outstanding Recognition:** Many established leagues for sports have created, in some form, an establishment to recognize the greatest retired competitors of their sport. Most often, this is known as the Hall of Fame, the clearest indication of greatness of past players. Our adapted model will add any players in a Hall of Fame to the contention pool.

(2) **Outstanding Accomplishments:** The next consideration for potential candidates comes in the form of outstanding accomplishments, which are loosely defined as victories in major competitions, scores/times/etc. that broke local or world records, or qualifications for major competitions or tournaments. Since current or newly retired competitors will not be in the Hall of Fame for their sport, this criteria is meant to filter out those players.

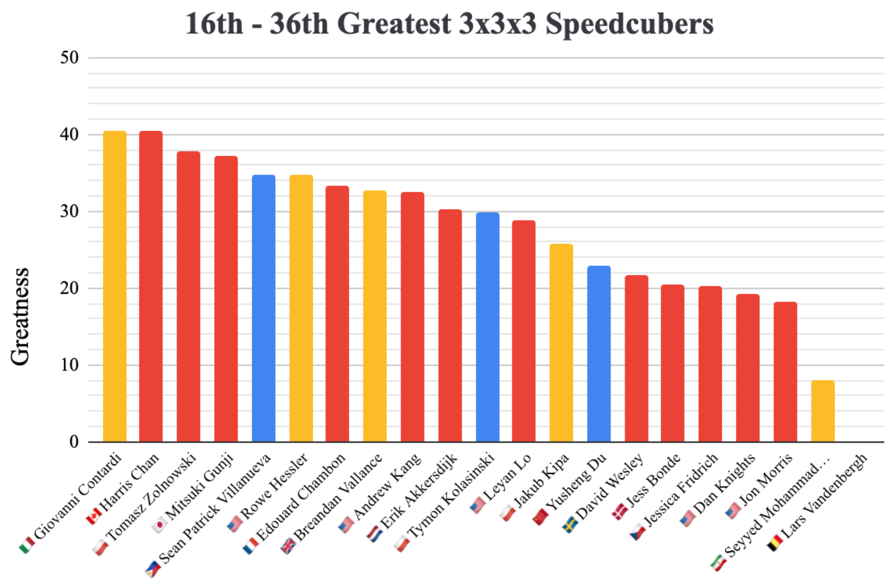

FIGURE 4. The remaining players had greatness score ranges from 40.549 to 0.000. Red represents peak years 2003-2009, yellow represents peak years 2010-2015, and blue represents players with peak years 2016-2021.

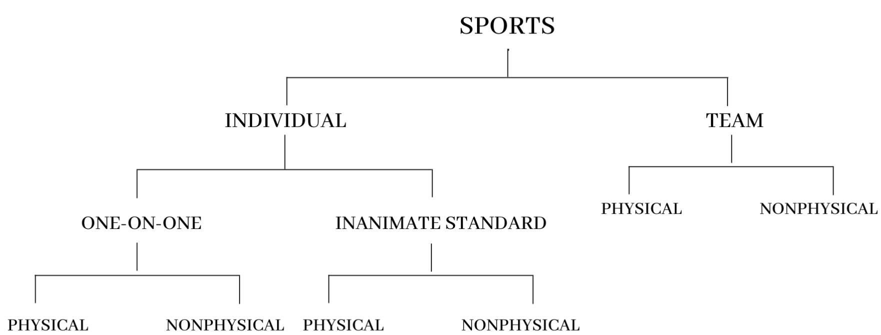

FIGURE 5. A simple tree distinguishing the types of sports that can be interpreted by models.

(3) **Outstanding Statistics:** Lastly, it is worth considering competitors with career statistics that place them near the top of all players. These players are incredibly skilled, but perhaps missed out on championships or Hall of Fame recognition for whatever reason. To determine statistics suitable for this distinction a sport will be divided into eras based on the changing nature of the sport. For example, the introduction of new training methods, technologies, improvements in science, etc. could increase the performance and statistics of players over time. Comparing players relative to their time period will ensure a fairness.

From here, comparison factor(s) for the standard of comparison must be developed. It is important to choose factors that capture the essence of what defines the sport and what makes it competitive. For example, in model 2a the comparison factor is the average solve times by year among candidates, since the standard of comparison for speedcubing is solve time. Any variables that most closely represent score, time, or any other standard of comparison should be turned into a comparison factor, with averaging or any other method of representing the pool of competitors holistically. Examples are:

(1) **Track and Field** For a sport like Track and Field the inanimate standard is the time it takes each competitor to complete their race. So, a comparison factor would be the average times of each race.

(2) **Gymnastics** In gymnastics, players are given scores based on the difficulty of their routines and the execution of their routines. Comparison factors could be average difficulty scores and average execution scores, or combined score. [2]

It is possible that the sport can vary significantly in different locations (for example, varying rules by country), so adjustments can be made to either make the standard constant throughout, or the testing pool can be divided by region. Note that this variance must be small enough to consider all activities the same sport. The Speedcubing model will be adapted to compare player's statistics (such as time, scores, etc.) with one **or more** comparison factors, generating the competition scores.

The model will use the same normal distribution curve to model improvement and decline past a player's peak for any nonphysical sport. We can use different constant for both the improvement and decline curve depending on the nature of the sport. For a physical sport, the athlete's body will inhibit their performance past a certain age, based on the sport. So, for each sport, the average time period of players' peaks can be taken, and then a curve can be modeled around the player's peak and the sport's duration of peak. With the curve and competition scores, a weighted average can be taken for the player's career over the years to determine his overall competition score, using weights according to the curve and scaled to sum to 1.

While the Speedcubing model accounts for world records for singles and averages in a separate score, this kind of additional greatness factor can be adapted into a more general structure, referred to as an "Impulse of Greatness." While a competitor with great competitiveness and success in their sport will be considered good, a player needs defining moments, impulses of greatness, to be considered great or even the G.O.A.T. Thus, impulses of greatness act to separate the very good players from the players worth considering for the G.O.A.T. In adapting the model there would be the option to add multiple types of these impulses.

A sample list of types of impulses follow, with descriptions on how they are set up:

(1) **Records:** Either world, regional collegiate, etc., records highlight the best measurement of scores, times, etc. ever recorded. Holding a record for an individual sport is a high achievement, and thus every instance of breaking a record will increase the

Greatness Score. Similar to the speedcubing model, these records will be evaluated for their duration of being held, their improvement on previous records, and will be kept in the context of their era of the sport.

(2) **Near-records and Great Performances:** While these achievements will not be rated as highly as those that broke records, near-records and outstanding personal bests still add to a player's greatness, especially when consistently produced.

(3) **Great Victories:** A defining moment for a competitor could be a victory against all odds. A great victory is defined as a victory that was unexpected, based on the player's statistics and expectations.

These Impulses of Greatness must all be chosen, quantified, and compared objectively and based on data, meaning that they are not chosen by popularity (a memorable, funny, or cool moment is not immediately an Impulse of Greatness, but oftentimes Impulses of Greatness can have these qualities). Choosing the Impulses of Greatness can be done by choosing a threshold on the degree of greatness of every any moment that could qualify as one. All records, should be considered, but near-records should come within a certain degree of a record. Great victories can be quantified by observing the probability of the player winning and converting it into a score.

So, a final greatness score can be calculated by multiplying all weighted competition scores and impulses of greatness, which will determine the G.O.A.T. of any individual sport with an inanimate standard.

5.2. **Adaptations for One-on-One Individual Sports.**

To model a one-on-one individual sport, elements from both the Women's Tennis model and Speedcubing model can be used and adapted. Since the Tennis model only accounts for one year of competition over 4 major tournaments, the model can be improved to span the entire history of the sport, which has been addressed in the Speedcubing model and the adapted model for any individual sport with an inanimate standard. The model follows this general structure:

(1) **Gathering Potential Greats:** This process will be exactly the same as the steps outlines for pooling players previously.

(2) **Gathering Matches to Analyze:** It is essential that the model samples data of player's wins, losses, scores, etc. from a standardized pool of matches. Most often this will consist of matches played under the most prominent league(s) for the sport. For example, the most prominent source of professional tennis matches is the ATP tour [5]. Data must be sourced that contains, at minimum, match results and scores.

(3) **Establishing Time Periods:** The model will observe how trends change over time and will relatively compare players across eras. The default time period of comparison

is set at 1 year.

(4) **Calculating Yearly Greatness Scores:** For each candidate, a yearly greatness score will be calculated with the model for Women's Tennis, using the data collected on matches. Each player will have a collection of competition scores for each year (or determined time period) that they compete.

(5) **Elevation and Degradation Curve to Compensate for Improvement and Decline:** Exactly like the model for individual sports with a inanimate standard, this model will account for improvement and decline around a peak, accounting for the boolean physically of the sport.

(6) **Impulses of Greatness:** The Impulses of Greatness will be applied on to the weighted average of competition scores. Examples for One-on-One Impulses of Greatness are great victories, records, and outstanding winning streaks.

(7) **Final Calculations:** So, similar to the Speedcubing model, the calculation of the Greatness Score is taken as the product of the competition score and each Impulse of Greatness.

6. Adaptations for Team Sports

To account for team sports, we devised a list of what makes a great team player:

(1) **Great Individual Performance:** The G.O.A.T. of team sports must be an outstanding player, **with respect to other players of their position.** To model this, we would use our model for **individual sports with an inanimate standard,** and set the standard (comparison factors) as the average statistics of all potentially great players in each position. We also can factor in any world records held by individual players. For example, a goalkeeper will be given an individual score with respect to all other goalkeepers in the pool of players. It is important to make this positional distinction since the role of position players and their subsequent statistics varies widely within many sports. For a sport without positions, all players will be compared with respect to universal standards, for obvious reasons.

(2) **Great Team Performance:** The greatness of a player's team is another consideration for that individual's greatness. Though it is possible, it is highly unlikely that a player on poorly-performing teams can be considered an all-time great, so our model reflects that. In the case that the two teams compete against each other, a model similar to the model for **one-on-one individual sports**, with the multi-year consideration of peak, improvement, and decline. Then, as a weighted average, the competition score of the team during the player's time on it is calculated. In the case of more than two teams competing, the variables would be adjusted to account for placement, rather than wins and losses (i.e. placing second out of 5 teams). Note that players on the same team will only have the same team competition score if all of

their years on the team are the same.

(3) **Value of Player:** In a team sport, another consideration is the value of the player to the team. How does the team perform with and without the player, and how would their success greatness change in the absence of the player? There are two scenarios to analyze in order to determine the value of player: (1) The comparative greatness of a team with and without the player **during the player's time on the team,** and (2) the comparative greatness of the team if the player was replaced with an average player on the team.

The first scenario is based on the pool of games of the team during the player's time can be divided based on whether or not the player competed in the games. Then, two team greatness scores can be taken over the two pools of games, and the difference between the two can be taken and converted into the first player value subscore.

To simulate the second scenario, the major yearly statistics of the player can be gathered, as well as team averages for those statistics **discluding the player** (team averages are done positionally if applicable). Examples of these statistics could be: Points per Game for Basketball, Runs Batted in for Baseball, Kills / Digs for Volleyball, etc. Then, the player is replaced on the team with another player in their position that has statistics equal to the team averages. With those changes to major statistics, the scores of every match in the model can be roughly changed based on the absence of the player, and the new greatness score can be generated. Then, by analyzing the difference between the new and old greatness scores, a second player value subscore can be generated.

So, with the combination of the individual greatness score, the competition score of the team, and the player value score taken by multiplying the subscores, the model can output a final greatness score of each player, and determine the G.O.A.T. of any team sport.

7. Letter to the Director of Top Sport

To the Director of Top Sport:

We are excited to announce the development of comprehensive models for women's singles tennis and 3x3x3 speedcubing which can be universally adapted to fit all individual and team sports. All models are tailored to return a definitive greatness score between 0 and 100 for any individual athlete relative to their opponents, regardless of sport played. By broadening or narrowing the scope of our players or the time, it is possible to determine the greatness of players in any geographical region, division of sport, or time period.

Our first model examines women's singles tennis in the year 2018, determining the relative greatness for all participants in the Grand Slam tournaments held that year. Each individual match was analyzed, with a domination score derived from the game score reflective of the players' performance. Matches were also weighted differently based on the round they were played in and the relative strengths of the two opponents. At the end of the match, the two opponents' greatness scores were increased by a total reflective of their performance in the match. We ran 1000 iterations of the four 127-game tournaments to obtain a definitive ranking of all 189 participants. Our model found the greatest women's singles tennis player in 2018 to be Simona Halep, which is clearly justified with her first Grand Slam Title at the French Open, Player of the Year Award by the WTA, and her ranking as first in the world. The model outputted Angelique Kerber, Naomi Osaka, Caroline Wozniacki, and Serena Williams to round out an impressive top 5.

In our second model, we decided to think outside the cube, and sought to find the greatest 3x3x3 Rubik's cube solver of all time. For an eccentric sport not dissimilar to sprinting, we solicited a pool of 36 world championship finalists and world record holders across the history of cubing. We compiled detailed records of their tournament results over their careers as well as their prestigious world record reigns, comparing performance with the saturation of the playing field for every year. After implementing a system to selectively emphasize a cuber's best years, we factored in extraordinary solves and world records to each individual's greatness scores over their career. In the end, the model returned the legendary Feliks Zemdegs as the undisputed G.O.A.T. of speedcubing (by quite a significant margin), followed by Max Park and Mats Valk.

The two models are based on principles common to many sports. Our tennis model can serve as a framework for any matchup-dependent individual sport, from boxing to bowling to badminton. Our speedcubing model can be adapted to any sport with an inanimate standard: triathlon, golf, weightlifting, ski jumping, and skeleton among these. What is perhaps most beautiful is the combination of these two to form a model for the greatness of individuals in team sports. Taking advantage of the solo greatness evaluated in the second model and the matchup greatness evaluated in the first model, individual and team performance and player value can build on a foundation, able to model field hockey, football, Fortnite and more.

Taken together, we believe our models of tennis and speedcubing to be very accurate and effective in calculating performance-based greatness, and would be eager to apply them to the great world of all sports.

Best regards,
Team US-10656

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8. Appendices

8.1. **Appendix A. Greatness of Women's Singles Tennis Players, 2018.**

Rank	Name	Greatness Score	Tournaments Played	Rank	Name	Greatness Score	Tournaments Played
1	S. Halep	100.000	4	40	M. Vondrousova	88.808	4
2	A. Kerber	99.411	4	41	V. Williams	88.711	4
3	N. Osaka	98.880	4	42	A. Bogdan	88.586	4
4	C. Wozniacki	98.394	4	43	Q. Wang	88.530	4
5	S. Williams	97.850	4	44	D. Gavrilova	88.353	4
6	M. Keys	97.315	3	45	L. Kumkhum	88.301	4
7	S. Stephens	96.409	4	46	M. Sakkari	88.118	3
8	D. Cibulkova	94.978	4	47	E. Svitolina	87.937	4
9	D. Kasatkina	94.892	4	48	M. Rybarikova	87.934	4
10	M. Sharapova	94.204	4	49	V. Azarenka	87.712	4
11	J. Gorges	94.127	4	50	B. Pera	87.001	3
12	Ka. Pliskova	93.915	4	51	S. Cirstea	86.864	4
13	J. Ostapenko	93.868	4	52	I-C. Begu	85.870	4
14	C. Suarez Navarro	93.657	4	53	D. Allertova	83.933	4
15	S-w. Hsieh	93.609	4	54	M. Linette	83.198	3
16	A. Sevastova	93.590	4	55	Z. Diyas	83.073	4
17	K. Bertens	93.513	4	56	E. Rodina	79.021	3
18	A. Barty	93.197	4	57	A. Radwanska	75.540	2
19	K. Kanepi	93.141	4	58	L. Arruabarrena	74.393	3
20	E. Mertens	93.002	4	59	S. Zhang	73.480	4
21	C. Giorgi	92.624	4	60	A. Sabalenka	73.388	4
22	D. Vekic	92.565	4	61	S. Sorribes Tormo	73.094	4
23	E. Makarova	92.448	4	62	T. Maria	72.819	2
24	A. Sasnovich	92.422	4	63	S. Zheng	72.796	4
25	B. Strycova	91.959	4	64	A. Petkovic	72.777	2
26	G. Muguruza	91.683	4	65	P. Kvitova	72.259	4
27	L. Tsurenko	91.646	4	66	K. Mladenovic	72.086	4
28	C. Garcia	91.280	4	67	Y. Wickmayer	68.340	4
29	M. Buzarnescu	91.003	4	68	M. Puig	67.765	3
30	B. Bencic	90.751	3	69	S. Stosur	67.016	3
31	R. Peterson	90.420	4	70	V. Diatchenko	63.297	4
32	A. Van Uytvanck	90.295	3	71	K. Muchova	62.259	1
33	A. Kontaveit	89.931	4	72	K. Flipkens	61.539	1
34	S. Kenin	89.538	4	73	K. Swan	58.454	4
35	S. Vickery	89.520	4	74	A. Riske	58.124	1
36	Y. Putintseva	89.471	3	75	M. Duque Marino	57.730	4
37	L. Safarova	89.335	4	76	T. Townsend	54.342	3
38	K. Siniakova	89.162	4	77	P. Parmentier	53.206	4
39	P. Martic	88.967	4	78	A. Cornet	52.903	4

79	J. Larsson	52.830	4	119	A-l. Friedsam	9.557	1
80	L. Davis	50.464	4	120	D. Aiava	9.556	1
81	Y. Duan	48.548	1	121	A. Kalinina	9.521	1
82	J. Brady	46.618	2	122	B. Krejcikova	9.477	1
83	K. Bondarenko	45.758	4	123	H. Dart	9.472	1
84	J. Konta	45.732	4	124	V. Tomova	9.454	1
85	K. Kozlova	45.269	4	125	B. Stefkova	9.438	2
86	A. Pavlyuchenkova	45.231	4	126	C. Bellis	9.429	1
87	M. Brengle	44.380	4	127	K. Dunne	9.424	1
88	S. Peng	44.252	4	128	K. Ahn	9.415	1
89	A. Krunic	43.944	3	129	D. Lao	9.407	1
90	V. Lapko	39.635	4	130	P. Schnyder	9.398	1
91	B. Mattek-Sands	38.027	2	131	W. Osuigwe	9.379	1
92	M. Kostyuk	32.670	1	132	G. Min	9.378	1
93	V. Zvonareva	14.608	1	133	L. Zhu	9.351	1
94	E. Bouchard	13.897	2	134	A. Lottner	9.323	1
95	N. Gibbs	13.853	3	135	N. Broady	9.285	1
96	T. Babos	13.746	2	136	N. Hibino	9.246	1
97	F. Ferro	13.607	4	137	I. Wallace	9.236	1
98	M. Frech	13.100	1	138	D. Chiesa	9.228	1
99	E. Vesnina	12.354	2	139	I. Jorovic	9.227	1
100	C. Liu	12.208	2	140	I. Falconi	9.207	1
101	J. Fett	12.001	2	141	M. Bouzkova	9.167	1
102	A. Dulgheru	11.946	2	142	D. Yastremska	9.166	1
103	M. Lucic-Baroni	11.574	2	143	A. Kalinskaya	9.125	1
104	V. Kuzmova	11.441	1	144	A. Rus	9.052	2
105	K. Boulter	11.349	4	145	J. Cepelova	9.050	3
106	G. Garcia Perez	11.025	1	146	V. Lepchenko	8.901	1
107	V. King	11.003	1	147	E-G. Ruse	8.900	3
108	A. Tomljanovic	10.994	2	148	A. Muhammad	8.884	1
109	J. Teichmann	10.885	4	149	M. Minella	8.868	1
110	O. Rogowska	10.882	1	150	J. Ponchet	8.830	1
111	F. Di Lorenzo	10.807	1	151	M. Georges	8.750	2
112	B. Haddad Maia	10.796	1	152	T. Zidansek	8.706	1
113	H. Watson	10.697	1	153	A. Anisimova	8.704	1
114	J. Glushko	10.636	4	154	R. Hogenkamp	8.675	1
115	A. Blinkova	10.626	1	155	X. Wang	8.521	2
116	C. Witthoft	10.558	3	156	S. Errani	8.480	1
117	M. Barthel	10.399	4	157	C. Paquet	8.441	1
118	M. Gasparyan	9.558	4	158	D. Collins	8.434	1

159	K. Nara	8.420	3				
160	K. Kucova	8.336	4				
161	S. Kuznetsova	8.246	2				
162	E. Alexandrova	8.189	3				
163	S. Vogele	8.138	4				
164	A. Hesse	8.110	3				
165	C. Vandeweghe	8.081	1				
166	H. Tan	7.941	4				
167	G. Taylor	7.913	1				
168	T. Bacsinszky	7.764	1				
169	M. Eguchi	7.408	1				
170	S. Rogers	7.396	1				
171	A. Konjuh	6.995	1				
172	O. Jabeur	6.952	2				
173	J. Fourlis	6.781	3				
174	T. Smitkova	5.871	1				
175	F. Schiavone	5.859	1				
176	D. Jakupovic	5.780	2				
177	V. Cepede Royg	5.759	2				
178	Kr. Pliskova	5.733	3				
179	Y. Wang	5.723	4				
180	C. Dolehide	5.506	3				
181	O. Dodin	5.406	3				
182	L. Cabrera	5.333	2				
183	N. Vikhlyantseva	4.818	2				
184	C. McHale	4.696	4				
185	L. Siegemund	3.856	4				
186	M. Niculescu	3.697	2				
187	P. Hercog	2.415	3				
188	AK. Schmiedlova	0.497	4				
189	V. Golubic	0.000	4				

8.2. **Appendix B. Additional Chart of Women's Singles Tennis Players, 2018.**

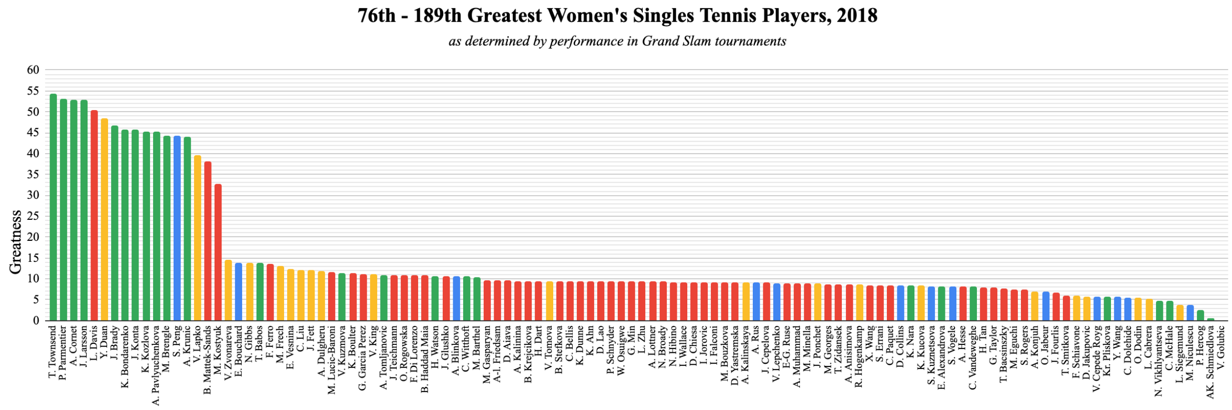

FIGURE 6. The remaining players had greatness score ranges from 54.342 to 0.000. Green represents players who participated in four Grand Slam tournaments. Blue represents players who participated in three, yellow for two, red for one.

8.3. **Appendix C. Python Code for Women's Singles Tennis Model.**

```
import csv
import random

files = ['All Tennis Games - Australian Open.csv',
    'All Tennis Games - French Open.csv',
    'All Tennis Games - US Open.csv',
    'All Tennis Games - Wimbledon.csv']

#interprets the spreadsheets into a list of games
def gameList(files):
    games = []
    for file in files:
        data_file = open(file, 'r')
        data = [line for line in csv.reader(data_file)]
        data.pop(0)
        while len(data) > 0:
            data.pop(0)
            p1 = data.pop(0)
            p2 = data.pop(0)
            if 'r' in p1 or 'r' in p2 or 'w/o' in p1 or 'w/o' in p2:
                continue
            if (int(p1[3]) < int(p2[3]) and int(p1[5]) < int(p2[5])) or
                    (not (int(p1[3]) > int(p2[3]) and int(p1[5]) > int(p2[5])
                    and (int(p1[7]) < int(p2[7]))):
                p1, p2 = p2, p1
            game = []
            game.append([p1[2],p2[2]])
            score = [[int(p1[3]),int(p2[3])],[int(p1[5]),int(p2[5])]]
            if p1[7] != '':
                score.append([int(p1[7]),int(p2[7])])
            if p1[4] != '':
                score[0].append([int(p1[4]),int(p2[4])])
            if p1[6] != '':
                score[1].append([int(p1[6]), int(p2[6])])
            if p1[8] != '':
                score[2].append([int(p1[8]), int(p2[8])])

            game.append(score)
            game.append(int(p1[1]))
            game.append(file)
            games.append(game)
```

```
    return games

games = gameList(files)

initial = 0.0
baseGain = 5
base = 5
logConst = 50
roundConsts = [1.2**i for i in range(7)]

#calculates the domination score based on the score of the match
def domScore(score):
    sum = 0.0
    for scor in score:
        tieFactor = 1
        if scor[0] + scor[1] == 13:
            tieFactor = (0.9889) ** min(scor[2][0] + scor[2][1]-7,20)/0.8
        if scor[0] < scor[1]:
            sum -= (0.8)**(scor[0]+scor[1]-6)*tieFactor
        else:
            sum += (0.8)**(scor[0]+scor[1]-6)*tieFactor

    return 1.5- (0.5/(1-.3**3))*(1-(0.3)**(2-sum))

ratings = {}
for game in games:
    ratings[game[0][0]] = initial
    ratings[game[0][1]] = initial

#puts the list of games through the rating system
def update(games):
    for game in games:
        r1 = ratings[game[0][0]]
        r2 = ratings[game[0][1]]
        try:
            ratings[game[0][0]] += baseGain *
                (1 - 1/(1+base ** ((r2-r1)/logConst)))/
                domScore(game[1])*roundConsts[game[2]]
            ratings[game[0][1]] -= baseGain *
                (1 / (1 + base ** ((r1 - r2) / logConst)))
                / domScore(game[1])/roundConsts[game[2]]
        except:
```

```
            print(r1,r2)


#runs through the games 1000 times
for i in range(1000):
    random.shuffle(games)
    update(games)

comps = {}
for game in games:
    if game[0][0] not in comps.keys():
        comps[game[0][0]] = set()
    if game[0][1] not in comps.keys():
        comps[game[0][1]] = set()
    comps[game[0][0]].add(game[3])
    comps[game[0][1]].add(game[3])

#decreases score if missed more than 1 tournament
for key in ratings.keys():
    ratings[key] *= 0.8**max(0,3-len(comps[key]))


names = ratings.keys()
scores = [ratings[name] for name in names]

zipped_lists = zip(scores, names)
sorted_pairs = sorted(zipped_lists)

tuples = zip(*sorted_pairs)
scores, names = [ list(tuple) for tuple in  tuples]

names.reverse()
scores.reverse()

scaled = [100*(score-scores[-1])/(scores[0]-scores[-1]) for score in scores]

#prints the sorted names and scores
for i in range(len(names)):
    print(names[i] + ", " + str(scaled[i]) + ", " +
        str(len(comps[names[i]])))
```

8.4. Appendix D. Greatness of Speedcubers.

Rank	Name	Greatness Score	Peak Year
1	Feliks Zemdegs	100.000	2010
2	Max Park	61.268	2018
3	Seung Hyuk Nahm	57.880	2018
4	Mats Valk	54.872	2012
5	Bill Wang	54.343	2016
6	Philipp Weyer	52.086	2016
7	Yu Nakajima	49.903	2008
8	Jean Pons	49.134	2006
9	Sebastian Weyer	48.814	2014
10	Patrick Ponce	48.379	2019
11	Lucas Etter	46.841	2017
12	Cornelius Dieckmann	46.776	2011
13	Michal Pleskowicz	45.533	2011
14	Yumu Tabuchi	42.550	2009
15	Shotaro Makisumi	40.594	2006
16	Giovanni Contardi	40.549	2011
17	Harris Chan	40.478	2009
18	Tomasz Zolnowski	37.880	2008
19	Mitsuki Gunji	37.133	2009
20	Sean Patrick Villanueva	34.809	2019
21	Rowe Hessler	34.789	2011
22	Edouard Chambon	33.352	2008
23	Breandan Vallance	32.685	2011
24	Andrew Kang	32.579	2008
25	Erik Akkersdijk	30.294	2009
26	Tymon Kolasinski	29.784	2019
27	Leyan Lo	28.780	2006
28	Jakub Kipa	25.826	2015
29	Yusheng Du	22.974	2020
30	David Wesley	21.661	2003
31	Jess Bonde	20.507	2003
32	Jessica Fridrich	20.349	2003
33	Dan Knights	19.340	2003
34	Jon Morris	18.176	2005
35	Seyyed Mohammad Hossein Fatemi	7.945	2015
36	Lars Vandenbergh	0.000	2004

8.5. **Appendix E. Competition Scores of Cubers, Visualized.**

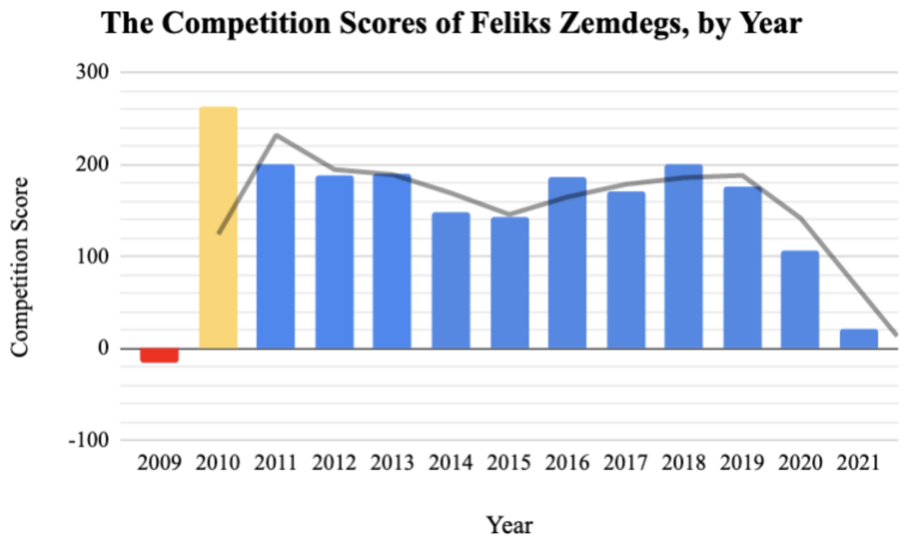

FIGURE 7. Our Speedcubing Model determined that Feliks Zemdegs is the G.O.A.T. by a significant margin. Visualized are his competition scores over the years, with the yellow column signifying his peak year, and blue and red representing positive and negative competition scores respectively.

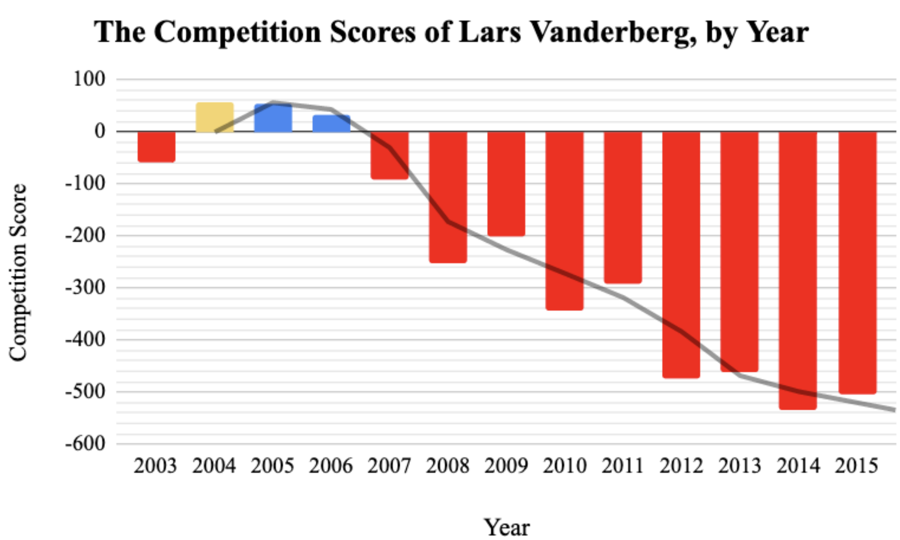

FIGURE 8. Our Speedcubing Model determined that Lars Vanderberg was the worst out of our pool of 36 cubers. Visualized are his competition scores over the years, with the yellow column signifying his peak year, and blue and red representing positive and negative competition scores respectively.

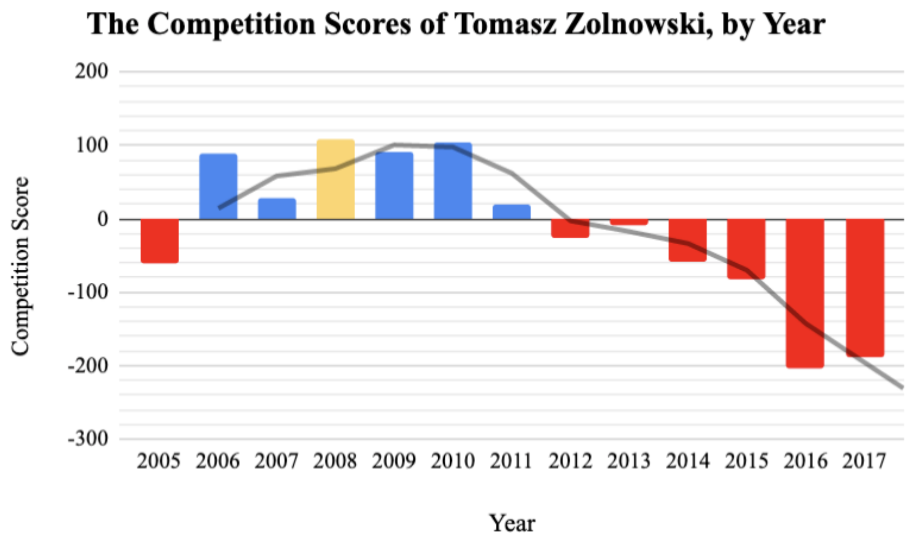

Figure 9. Our Speedcubing Model placed Tomasz Zolnowski in the middle of our pool of 36 cubers, at rank 18. Visualized are his competition scores over the years, with the yellow column signifying his peak year, and blue and red representing positive and negative competition scores respectively.

8.6. Appendix F. Python Code for Speedcubing Model.

```
import csv
import math
import numpy

data = [line for line in csv.reader(
    open("Model 2_ Speed Cubing - Stats 2.csv",'r'))]
data.pop(0)

ratings = {}
peaks = {}
numperyear = {}

person = ""
sum = 1.0
wsum = 1.0

#computes competition score for each person
while True:
    row = data.pop(0)
    if row[6] != '':
        numperyear[int(row[6])] = int(row[10])
```

```
    if person != row[11]:
        ratings[person] = sum/wsum
        if row[11] == '':
            break
        person = row[11]
        sum = 0.0
        wsum = 0.0
    peaks[row[11]] = int(row[23])
    sum += float(row[13]) * math.e **
        (-(int(row[12]) - int(row[23]))**2/100)
    wsum += math.e ** (-(int(row[12]) - int(row[23]))**2/100)

del ratings[""]

data = [line for line in csv.reader(
    open("Model 2_ Speed Cubing - Stats 3.csv",'r'))]
data.pop(0)

record = {}
for key in ratings.keys():
    record[key] = 1

#computes record score for each person
while True:
    row = data.pop(0)
    if row[0] == '' and row[14] == '':
        break
    if row[0] != '':
        record[row[0]] += (((1.0/float(row[5])) *
            (1+0.01*numperyear[int(row[1][-4:])])) - 1) *
            float(row[4])/365.0 / 5
    if row[14] != '':
        record[row[14]] += (((1.0 / float(row[18])) *
            (1 + 0.01 * numperyear[int(row[13][-4:])])) - 1)*
            float(row[17]) / 365.0/5

#combines the competition and record score
for key in ratings.keys():
    ratings[key] *= record[key]

people = ratings.keys()
scores = [ratings[person] for person in people]
```

```
zipped_lists = zip(scores, people)
sorted_pairs = sorted(zipped_lists)

tuples = zip(*sorted_pairs)
scores, people = [list(tuple) for tuple in  tuples]

people.reverse()
scores.reverse()
scaled = [100*(score-scores[-1])/(scores[0]-scores[-1]) for score in scores]

#prints sorted names, scores, and peak years
for i in range(len(people)):
    print(people[i] + ", " + str(scaled[i]) + ", " + str(peaks[people[i]]))
```