2025 WFTDA Rankings Algorithm update proposal

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tl;dr

The proposed algorithm calculates rankings by taking into account all games played by all teams in a region for the season at once. It uses a statistical method called “linear regression” to find the rankings for each team that best explain game results. Seeding games are no longer needed.

Simple explanation

Why it works

The 2023 algorithm calculated the rankings point contributions for each game, at the time of the game, based on the previous month’s rankings. Instead, the proposed algorithm evaluates *all* games played in the *whole* season for *each* new rankings release.

For example, If the Apples played the Bananas yesterday, then the Bananas play the Coconuts today, today’s game gives us new data about the Bananas and Coconuts, but it also helps put *yesterday’s* game in context so that we now know more about the Apples too. The advantage of the new algorithm is that it will re-evaluate yesterday's game with the new information.

At the end of this document you can find how the April 1, 2025 rankings would look with the proposed algorithm.

What does not change?

- “Close” games are determined in the same way (see 2023 algorithm [explainer doc])
- Predicted game score ratios can be determined by dividing teams’ current ranking points
- Obtaining a better score ratio than predicted will tend to increase your ranking

What changes?

- No more seeding games
- Games that are not “close” (with score ratios higher than 4:1) are expected to have a greater error between the assigned ranking and the actual score ratio and are weighted lower. This acts similar to the previous 4:1 cap, but is not identical.
- Calculating a single game’s impact (or potential impact) on rankings in isolation is no longer possible (because it depends on every other game too).
- Rankings no longer “accumulate” month-to-month with each game’s points set in stone at the time the game is played. In the new algorithm, the same set of games played at different times during the season will result in the same rankings.
  - As a result of this, playing a team that is over- or under-ranked at the time of the game no longer has a lasting effect on a team’s ranking.

How it works

The proposed algorithm uses a statistics concept called **Linear Regression** to find the best ranking that explains all teams’ game outcomes over a season. Features:

- Rankings calculations for each month take into account all in-region games all teams have played for that season, not just games between a team and their direct opponents.
- A team’s previous month's ranking is no longer centered for future rankings, it’s just a snapshot. Thus:
  - A team’s ranking points might shift in a new rankings publication even if they have not played a game.
  - This creates 12% more accurate rankings when tested with 2023-2025 games.

No rankings system can perfectly describe every game played in a region. By minimizing the difference (error) between *all* real game results and the rankings assigned to each team, we get the most optimal rankings to explain those results. To do this, we use a variation of a method described by Massey (1997) and previously implemented for roller derby by Sam Skipsey. This method allows us to leverage common statistics software libraries (eg. Python’s statsmodels) to perform the complex rankings calculations that minimize the error between the rankings and real-life results.

The 2023 algorithm took each game and found an *exact* ranking that explained that *single* match based on games played before it. Each of those single match rankings was then averaged to *estimate* the team’s new ranking. In the proposed algorithm, an *estimated* ranking is calculated for each team using *every game from every team across all of the season*. The new way is more accurate because it sees the larger picture.

Detailed Explanation

Current Situation

When WFTDA restructured the competitive play system for 2023, we used the opportunity to introduce a new rankings algorithm in order to accommodate regions and to resolve some problems the pre-Covid algorithm had exposed. Main goals:

1. **Regional independence:** ranking regions should be independent of each other.
2. **Single season:** post-season qualifications should be determined based on the complete season, without prior seasons' results having a significant effect.
3. **No guaranteed outcomes:** there should not be matchups where one team is guaranteed to worsen their ranking no matter how well they play, as was the case in the pre-Covid algorithm.
4. **Reasonable caps:** in a blowout game the algorithm should not incentivize squeezing out every last point.
5. **Results-based:** A game's effect on the rankings should only depend on the performance of teams in the region and the games that they play. Examples of other factors:
    a. With the pre-Covid algorithm, "how late in the season it is" had an effect on rankings: Strength factors depended on how many rankings points the team in the middle of the rankings had, which varied over the course of a season. It usually happened that games played late in the season got more rankings points for the same performance, but the magnitude of this effect varied and could theoretically end up being inverted (earlier games receiving more rankings points).
    b. Over-ranking affected a team *and* teams they played: When a team is under or over ranked at the time of a game in both the pre-Covid and 2023 algorithms, it affects the opposing team's ranking in a way that is not related to their performance.
6. **Outcome planning:** For season planning and pre-game goals, it should be easy for teams to determine what result they have to achieve in order to keep or improve their ranking.
7. **Accuracy for all teams:** The algorithm should be as accurate as possible for all teams in the region. (The pre-Covid algorithm was much less accurate for lower-ranked teams than higher-ranked teams due to the minimum strength factor distorting the points.)

The 2023 algorithm achieved many of these goals:

- #1 (regional independence) was already addressed in the pre-Covid algorithm (and the 2023 algorithm didn't change that)
- #2 (single season) was addressed by averaging over the games in the current season instead of a rolling window
- #3 (no guaranteed outcomes), #4 (Reasonable caps), and #7 (accuracy for all) were addressed by adding in a cap for games beyond which the exact score did not affect the game points

- #3 (no guaranteed outcomes), #5a (results-based, strength factor variability), #6 (outcome planning, and #7 (accuracy for all) were addressed by using the rankings points ratio as predicted score ratio directly instead of using an intermediate strength factor

We were *not* able to address #5b (results-based, over- under-ranked) in the 2023 algorithm.

For details of the 2023 algorithm refer to the existing explainer doc.

Problems

Unfortunately, the 2023 algorithm also introduced some new problems:

8. **Seeding games:** new teams entering rankings needed to play a seeding game against an already ranked team. This game needed a less than 10:1 score ratio and would not count towards the already ranked team's rankings. Lining up such a game can be more difficult than we anticipated for some teams, and especially in the GUR a number of teams forgot this requirement.
9. **Start-of-season surprises:** When a game's outcome is surprising (not really reflecting of the two teams' skills), and it's one of the team's first results in a new season, it has an outsized impact on rankings. This puts teams in a situation where they struggle to book appropriate games and other teams' rankings are affected, especially due to the effects of #5b still being unaddressed (over or under ranking of a team at the time a game is played).

These were significant problems that Membership raised which need to be addressed. Given feedback from some teams, it may even be warranted or necessary to change the algorithm in the middle of the current (2024-2026) season.

Proposed algorithm

Basic Idea

The key idea of our proposed algorithm is to evaluate *all games from all teams* in a region at once, determining the rankings that best match all results. This would move away from evaluating each game on its own based only on information available at the time of the game.

- #5b (results-based, over- under-ranked) and #9 (start-of-season outliers) will be addressed as teams' rankings at the time of the game no longer factor into the newly calculated rankings.
- #8 (seeding games) is addressed since we can now draw information about both teams from a team's first game - no more need for seeding games

This approach was initially proposed and implemented by Sam Skipsey for his SRD Rank algorithm. He determined it gave more accurate predictions than other commonly used sports ranking algorithms (see this blog post).

We modified the SRDRank algorithm in 4 ways:

- Connected all teams in a region, whether they have played each other or not, using the concept of a “virtual team”. We had to do this because our “regular season” doesn’t enforce that every team plays every other team, as is the case in most other sports. See Virtual teams below.
- Removed weights based on how recently a game was played in order to achieve #2 (single season).
- Added a diminishing weight for games with a score ratio over a cap (set at 4:1 like the previous cap). See Caps/ Diminishing weight below.
- We calculate GUR rankings based on all games played in all regions instead of defining GUR as a separate region. See GUR rankings below.

Similarities

A number of aspects of the 2023 algorithm remain the same in the proposed algorithm:

- The “meaning” of a team’s rankings points number remains roughly the same
    - We could switch now and a rankings points average of 450 in the old system would be similar to 450 RP in the new system.
    - The ratio of two team’s rankings points indicates the predicted result when they play a game. If a team achieves a score ratio better than predicted, their ranking will improve.
- RP *between regions* remain incomparable and will continue to indicate a different actual strength.
- “Close game” requirements to qualify for the postseason will remain the same
    - Criteria for when a game is considered does not change
    - A team has to play at least 5 close games in a season in order to be eligible for Regional Championships.
- Teams switching regions will work in the same way and have the same effects.

See previous explainer doc.

Side effects

The proposed algorithm has some side-effects:

- **Cannot calculate impact of a single game in isolation:** with the 2023 algorithm, computing a team’s new ranking points (RP) after a game only requires that team’s results along with their opponents’ RP on game day. With the proposed algorithm, each team’s RP depend on all results in the region, including games played later that month, and games played by other teams.
- **Ranking at the time of a game does not matter:** with the 2023 algorithm, a team’s ranking at the beginning of the month determines the RP contribution earned during that month, which is then accumulated across the season. This meant a team’s ranking at the time of a game (which was imperfect) influenced ranking results. With the proposed algorithm, we look at all the games during the whole season so there is no consideration

of the current RP at the time the game is played. This becomes especially obvious with games played at tournaments across a month boundary - with the 2023 algorithm the final ranking would be different if the games were swapped between tournament days (with the same scores), with the proposed algorithm that will no longer be the case.
    - Note: This is more accurate and removes the start-of-season outlier problem, but it is a significant change!
- **Easier to combine regions:** For regions that are sufficiently well-connected through GUR games, we could merge these regions using internally calculated GUR rankings as seedings. Merging is possible mid-season in case of necessity (eg. border crossing issues).
    - Currently NA regions appear sufficiently well-connected with each other, and Membership has asked us to think about combining NA, which would be much easier if we used the proposed algorithm.

Transition

Between seasons: Because the meaning of rankings points remains the same, switching algorithms in-between seasons is straightforward. The end of season rankings computed with the 2023 algorithm can just be used as seeds for the proposed algorithm as-is. Similarly, switching back to the 2023 algorithm between seasons would be just as easy.

Mid-season: Since each new rankings release reevaluates all games played in the current season, switching mid-season is easy by reusing the original seedings. (You can get an idea of how big the change would be from the sample rankings at the end of this document.) The resulting rankings will be the same as if the switch had happened at the start of the running season. Switching back mid-season would require more effort but can also be done by retroactively calculating all intermediate rankings.

GUR Rankings

We calculate GUR rankings the same way -- but we also include all games played across all regions instead of “just" GUR games. In the published rankings, only teams that have played GUR games will be included in GUR rankings. This removes the need for teams to have a seed in the GUR. Based on our evaluations on 2023-2025 game data, this also improves the prediction accuracy for GUR games by about 30%!

Full Mathematical Analysis

Basic setup

For each game between the “home” team and the “away” team, we try to match predicted score ratio and actual score ratio, so

$$\frac{RP\ home}{RP\ away} \overset{!}{=} \frac{score\ home}{score\ away}$$

In practice there will not be a set of rankings that allows this equation to be matched exactly for each game, so we will have to find an approximation that minimizes the errors.

We would like to use linear regression to solve this, however we are working with score ratios and ranking points ratios, which are multiplicative. In order to convert these ratios to be additive, we take the log. Note: the log of any ratio is the difference between the log of the top and the log of the bottom. This changes our equation above into:

$$ln\left(\frac{score\ home}{score\ away}\right) \approx\ ln\left(\frac{RP\ home}{RP\ away}\right) = ln(RP\ home) -\ ln(RP\ away)$$

Let’s simplify our equations by saying:

s = log of the score ratio for a game

r = log of a team’s RP (ranking points)

$$s_{game} \approx\ r_{team1} -\ r_{team2}$$

Because we know that the calculated RP will not perfectly match every games score ratio, we can write the equation for each game between team1 and team2 as:

$$\boxed{s_{game} = r_{t1} - r_{t2} + \varepsilon_{game}}$$

Where ε is an error term that will make the rank estimations perfectly match the game score.

Let’s set that equation aside for a moment and come at it from a different angle. Could we use linear regression to find a ranking for every team in the region? To do that, we would need to create linear equations that show the contribution of every team to each and every game in the season. Let’s say we have n teams. For every game we have to create an equation like:

$$s_{game1} = x_1 r_{t1} + x_2 r_{t2} + x_3 r_{t3} + x_4 r_{t4} + \ ...\ + x_n r_{tn} + \varepsilon_{game1}$$

$$s_{game2} = x_1 r_{t1} + x_2 r_{t2} + x_3 r_{t3} + x_4 r_{t4} + \ldots + x_n r_{tn} + \varepsilon_{game2}$$

where the score ratio (s) for each game is equal to a sum of contributions from every team (xr) that is dependent on each team's individual ranking.

Imagine these equations for hundreds of teams and thousands of games!

Luckily, we can simplify these equations using a trick described by Massey (page 32) to manipulate the x terms. Because each game is only played between two teams, we can set x to be 0 for all other teams that aren't implicated in a score ratio. Furthermore, if we set the x for the "home" team to be 1 and the x for the "away" team to be "-1", we create an equation like:

$$s_{gameAB} = 0 + 0 + r_{tA} - r_{tB} + \ldots + 0 + \varepsilon_{gameAB}$$

Or simply:

$$s_{gameAB} = r_{tA} - r_{tB} + \varepsilon_{gameAB}$$

Which is the same equation we had from above!

Summary so far:

- Create a system of linear equations, one for every game
- Every equation (game) has a term for every team in the region
- Set the x value for each team to:
  - 1 if the team is the home team
  - -1 if it's the away team
  - 0 if the team does not play in the game

Two more things to do before actually calculating the rankings: applying caps and adding virtual teams.

Caps / Diminishing weights

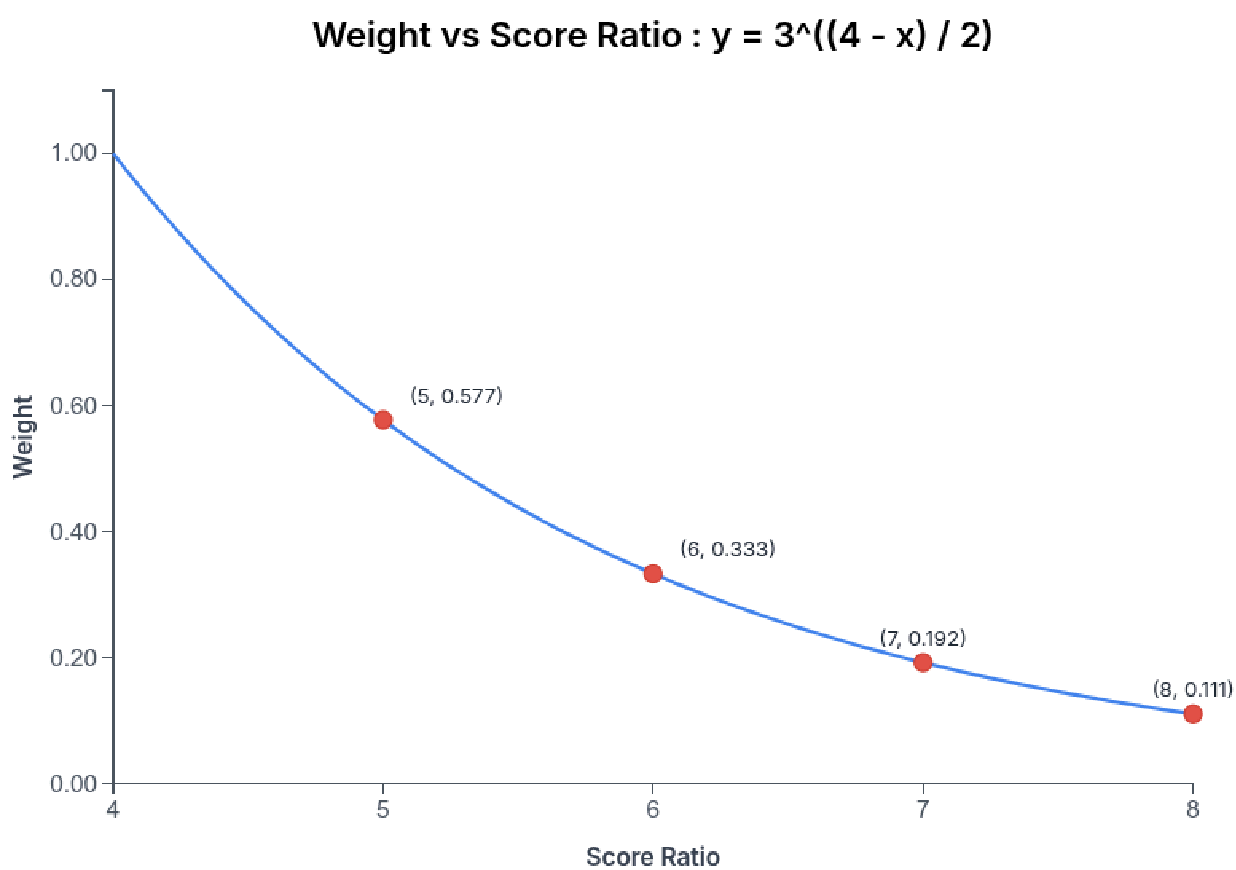
In the 2023 algorithm, we had a per game score ratio cap. To partially achieve the same effect, we put a reduced weight on the error term for games over cap. When we try to minimize error over the system, that game's error will count for less. In other words, we say that the error for a game over cap is *expected* to be higher than other games, so don't allow the game to affect calculated RP as much.

The equation becomes:

$$s_{gameAB} = r_{tA} - r_{tB} + \varepsilon_{gameAB}\omega_{gameAB}$$

Where ω is a weight of 1 for regular games and less than 1 for games over cap.

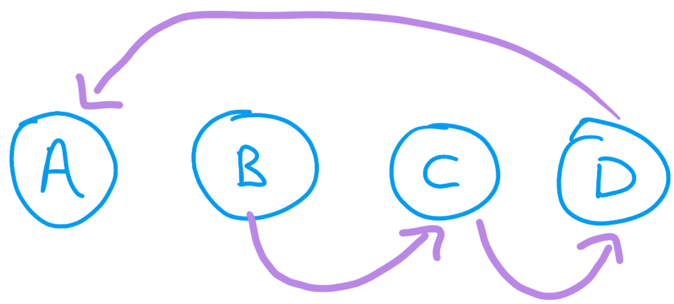
For games beyond a score ratio of 4:1, we use a weight of $3^{\frac{4 - score\_ratio}{2}}$, capped at a minimum of $\frac{1}{1,000,000}$ if the formula would yield a smaller weight (which happens for score ratios beyond about 25 : 1).
In that formula the 4 ensures that the weights seamlessly reach 1 at the cutoff ratio of 4:1. The 2 in the denominator of the exponent and 3 in the base combine to set a weight of $\frac{1}{3}$ at a ratio of 6:1, ensuring the zone where games transition from contributing to a team's ranking in a meaningful way to only being relevant if a team has no closer games starts around that 6:1 score ratio.



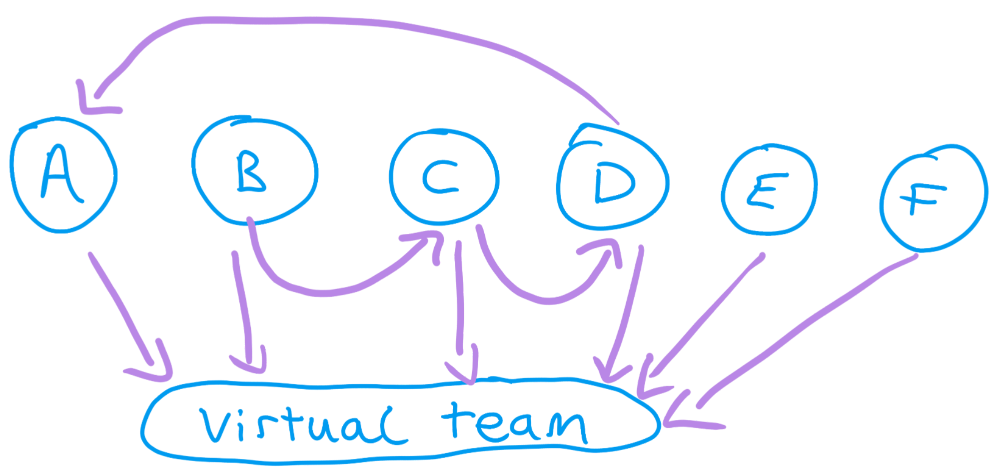
Note: the score_ratio for this calculation is taken as winner_score / loser_score so it is always greater than 1.

Virtual Teams

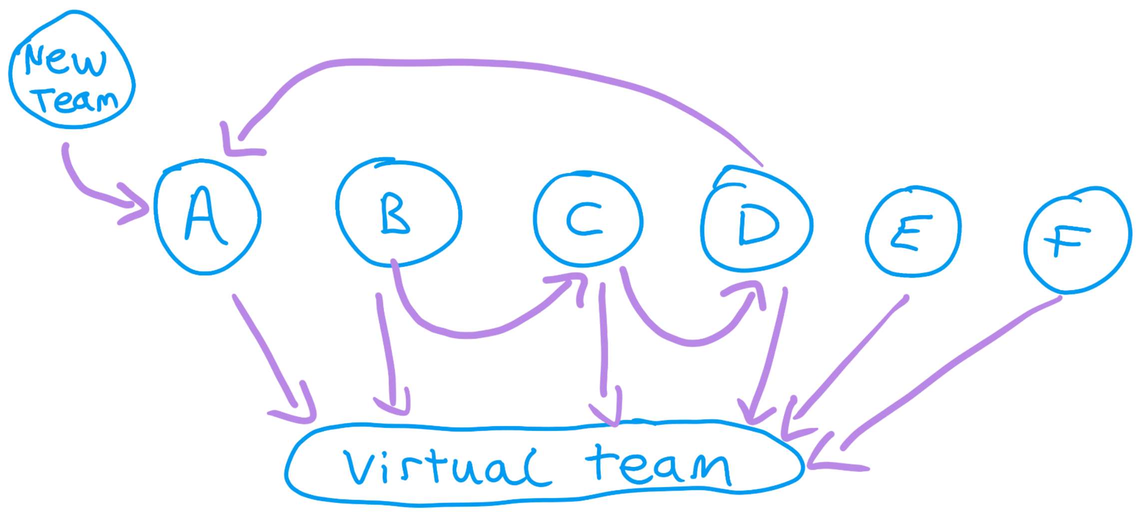
The original Massey proposal and SRDRank algorithm require all ranked teams in a region to be connected through games in the current season. “Connected” here means that for any pair of teams A and B they either need to have played each other directly or there needs to be some chain of teams that have played each other that leads from A to B. Eg. B->C, C->D, D->A would link up A and B.



Since in the WFTDA, teams can choose their games freely, we cannot guarantee all teams will be connected. In order to work around this problem we introduce *virtual games*. We create a *virtual team* with RP set to 1.00 that plays an imaginary game against each and every seeded team. The result of the game is <team seeding> to 1. These virtual games make sure that a connection as described above exists for each pair of teams as every team has “played” the same virtual team. For example, let’s imagine team E and F had not played A, B, C, or D. We “connect” them via the virtual team.



For newly joining teams that are not seeded, we ensure connection by requiring them to play against an already ranked team in the month they play their first sanctioned game. That game counts as a regular game. Ie. no seeding game. This will add them to a “chain” without needing to add a virtual game.



Takeaway: teams joining a region don't need to play a seeding game. The only requirement is that at least one game in their first rankings month must be against an already ranked team in the region and then that game and all their other games will count as regular games.

Note: Treating virtual games the same way as regular games causes a teams' rankings to be pulled towards their seed.

- This is desirable for teams that have played only a small number of games, in which case it helps address #9 (start-of-season outliers) above.
- Once a team has played 5 close games, this effect is no longer desired - we want the team's RP to only be determined by their actual games when deciding postseason invites. To minimize the effect of the seed, we reduce the weight of the virtual game to only 1/1,000,000 instead of 1 once the team has reached 5 close games.

Calculation

The system of linear equations representing all the games in a season, with the appropriate weights, can be solved using a weighted least squares regression (WLS) function. Functions to do this are available in common statistics software libraries like Python's statsmodels.

So, in our equation above:

$$s_{gameAB} = r_{tA} - r_{tB} + \varepsilon_{gameAB}\omega_{gameAB}$$

WLS can be used to determine values for each r so that $\sum_i \varepsilon_i^{\,2}\omega_i$ is minimized.

Note: because $ln(score\ ratio)$ is undefined if either team's score is 0, we treat a score of 0 as 0.1 for our calculations. A blowout game like this will have a very low weight anyway.

We are working with game score *ratios* and RP *ratios* (multiplicative). In these calculations, we must be in the linear regression space (additive). To do that, we have used the **natural log** of score ratios to calculate the **natural log** of RP.

Remember to **convert back** resulting r values by raising e to power of the result, eg.

$$e^{r} = e^{ln(rank\_team)} = rank\_team$$

Implementation

Construct 3 matrices for n games and j teams:

- Y = [n x 1] matrix that holds the log score ratio of every game : $ln\left(\frac{score\ 1}{score\ 2}\right)$.
  - Also include virtual games.

- X = [n x j] matrix where each row is a game and the columns are set to:
  - 1 if a team was team 1 in the game or it's the virtual game for that team
  - -1 if they were team 2 in the game
  - 0 if they didn't play

- W = [n x 1] matrix with a weight value that describes how much we think this game might deviate from the average rank.
  - Normally: 1
  - If over cap: $max(3^{\frac{4 - score\_ratio}{2}}, \frac{1}{1,000,000})$
  - If a virtual game and team has more than 5 close games: $\frac{1}{1,000,000}$

Plug these values into a WLS math function, for example Python's statsmodels.WLS. This will produce a [j x 1] matrix with the log ranking points of each team : $ln(RP)$.

Here's an example of 3 teams that play 4 games:

Games between the Apples, Bananas, and Coconuts

- `Apples   (100) vs Bananas  (50),  score ratio = 2`
- `Bananas  (120) vs Coconuts (100), score ratio = 1.2`
- `Apples   (150) vs Coconuts (50),  score ratio = 3`
- `Coconuts (60)  vs Banana   (80),  score ratio = 0.75`

```
    |    ln(2) |   |  0.693 |        |  1 -1  0 |          | 1 |
    |  ln(1.2) |   |  0.182 |        |  0  1 -1 |          | 1 |
Y = |    ln(3) | = |  1.099 |    X = |  1  0 -1 |      W = | 1 |
```

```
    | ln(0.75) |   | -0.287 |         |  0 -1  1 |          | 1 |

Result = statsmodels.WLS(Y, X, W).fit().params

         |   ln(RP_apples) |     |  0.597 |
Result = |  ln(RP_bananas) |   = | -0.164 |
         | ln(RP_coconuts) |     | -0.433 |
```

Rank	Team	RP
1	Apples	181
2	Bananas	85
3	Coconuts	65

Python code:

```
import statsmodels.api as sm
import math

RANKING_SCALE = 100 # add scale since we are not using seeds here
Y = [ math.log(100 / 50), math.log(120 / 100), math.log(150 / 50), math.log(60 / 80) ]
X = [ [1,-1,0], [0,1,-1], [1,0,-1], [0,-1,1] ]
W = [ 1, 1, 1, 1]

result = sm.WLS(Y, X, W).fit().params
rankings = [ math.exp(log_result) * RANKING_SCALE for log_result in result ]
print("Team rankings: " + str(rankings))
```

Appendix A: Visualizing Linear Regression

We do a *multivariate* linear regression, meaning we have as many contributing terms in each linear equation as we have teams in a region. This is difficult to visualise. For example, with 11 teams, we would need a 11-dimensional picture. However, a good sense of what is happening can be gained by looking at simpler linear regression systems. Let's start easy and build up in 4 steps.

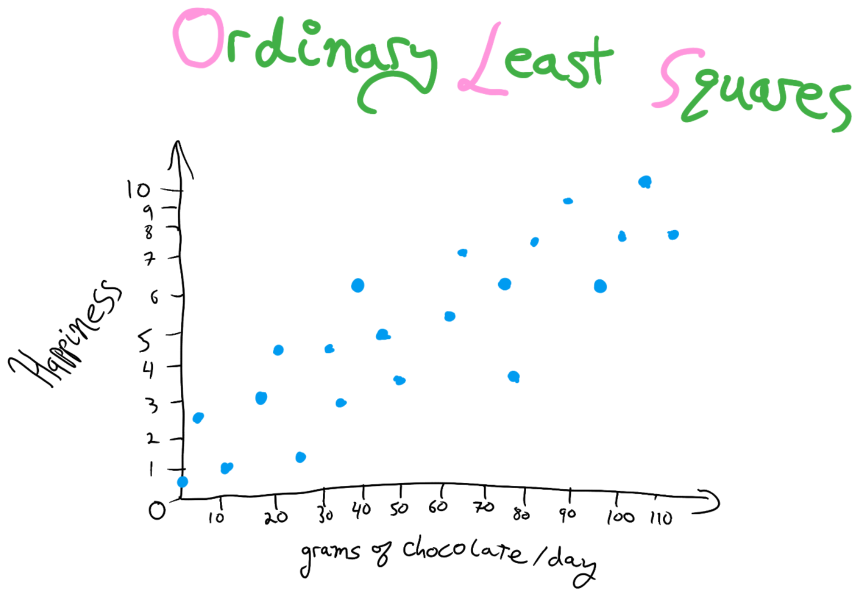
Terms:

- Linear : literally a "Line". We are trying to find a "best fit" line for given data.
    - Often written y = mx + b, where m is the slope and b is the y-intercept
    - In Linear regression we are usually solving for "m" - the slope.
- Regression : outlying data tends ("regresses") toward a mean
- Least squares : trying to minimize the square of error terms. $\sum_i \varepsilon_i^2$
- Ordinary : no special weighting term involved
- Weighted : a special "weighting" term is added to describe the magnitude of expected error
- Single variable : only one x term (independent variable) that affects the outcome (y is also known as the dependent variable)
- Multivariate : an outcome that is determined by more than one independent variable. In our case: a game outcome (y) is dependent on the strength of two teams (x1 and x2).

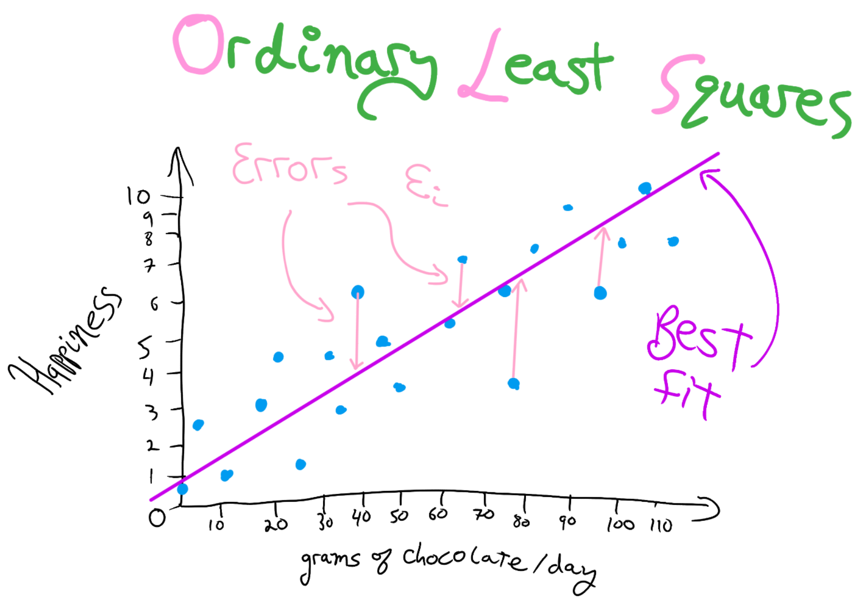
Ordinary Least Squares - single variable

One of the easiest linear regression systems to visualise is a signal variable situation where "ordinary least squares" (OLS) is applicable.

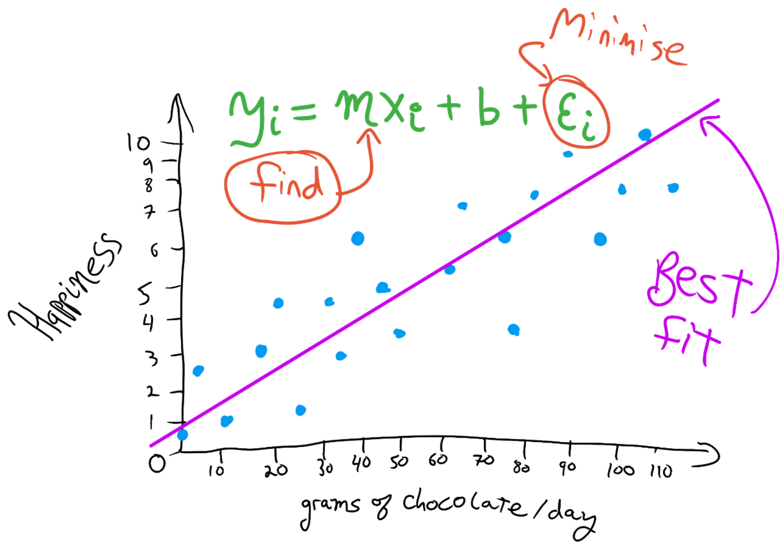
- Data looks to have a linear relationship between inputs and outputs
- Error between the best fit line and observed data does not vary as x gets bigger



Here we have some data gathered about people's happiness based on how much chocolate they eat. It looks linear (more chocolate == more happier)



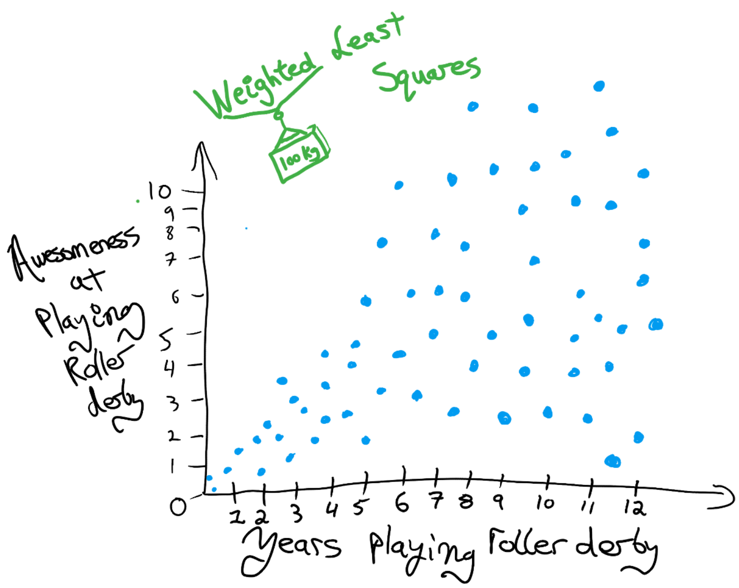
OLS lets us draw a line that best fits the observed data. It works by looking at all the differences (errors) between the calculated line and the real observed data.



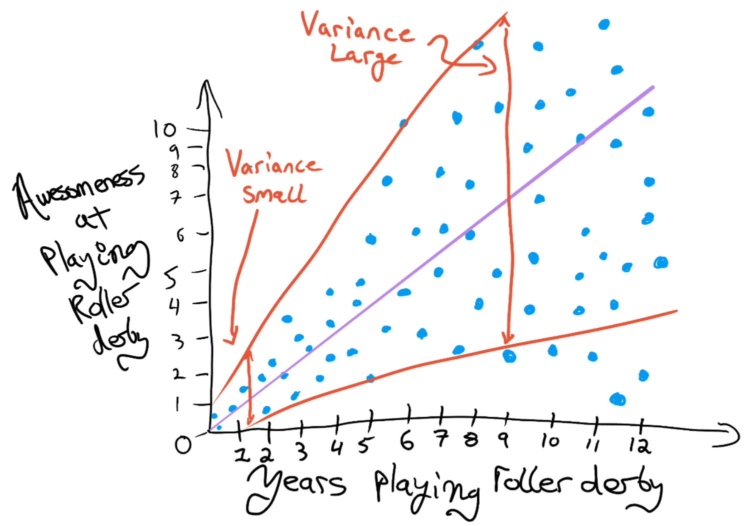
*Mathematically, we are looking for the **slope** of that line so that it minimizes the sum of all the error terms squared.*

Weighted Least Squares - single variable

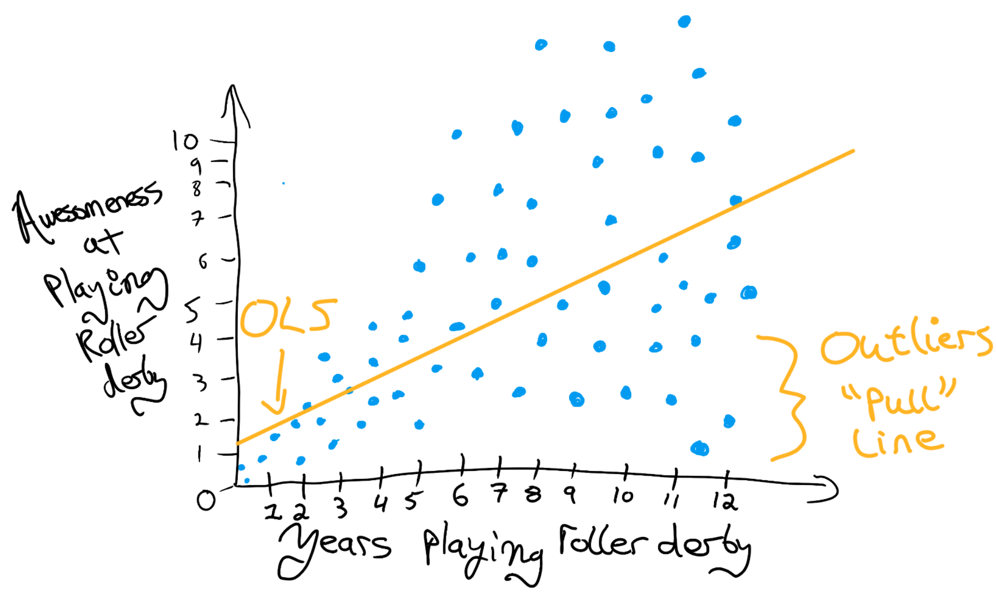
Not all data will fit this nice distribution. Oftentimes, the relationship between two things looks linear except that as x gets larger, errors tend to grow (or shrink). We can address this by adding a weight multiplier to the error term. This is called "weighted least squares".



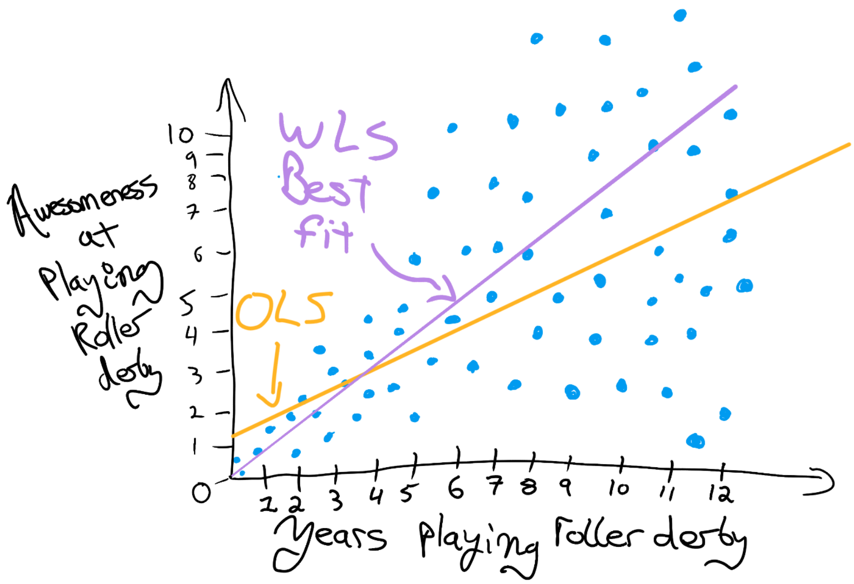
Here is some (fake) collected data about how awesome people are at roller derby based on how long they have been playing. It "sort of" looks linear, but there is a lot of variance in how skill progresses as time goes on (having babies, injuries, retirement / unretirement, level of play…)



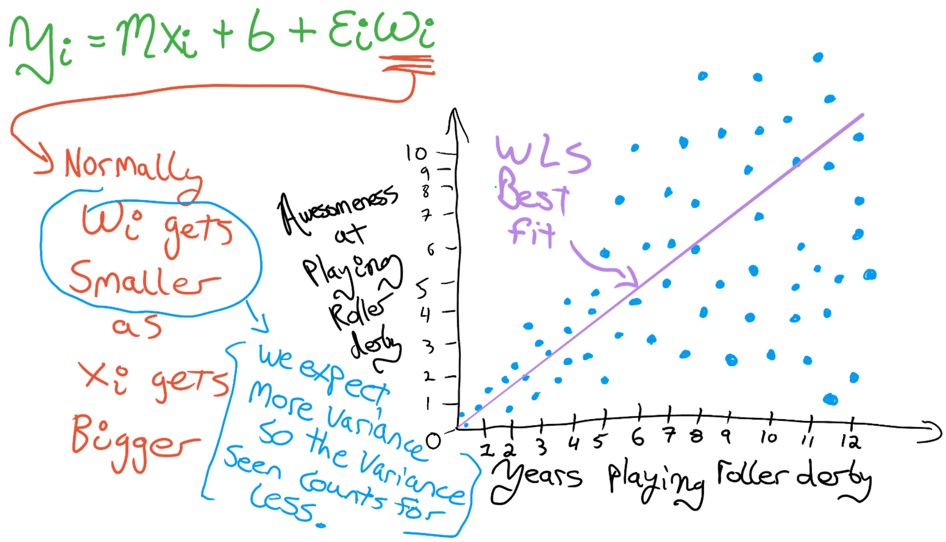
That "variance" in the awesomeness level gets bigger as the number of years goes up.
*We can draw a **better** best fit line than with OLS by taking into account that increasing variance.*



OLS will consider all variations equally and so large variations as number of years go up will "pull" the line strongly and override earlier data



WLS takes into account the expected greater variance later one an allows for a line that better fits all the data.

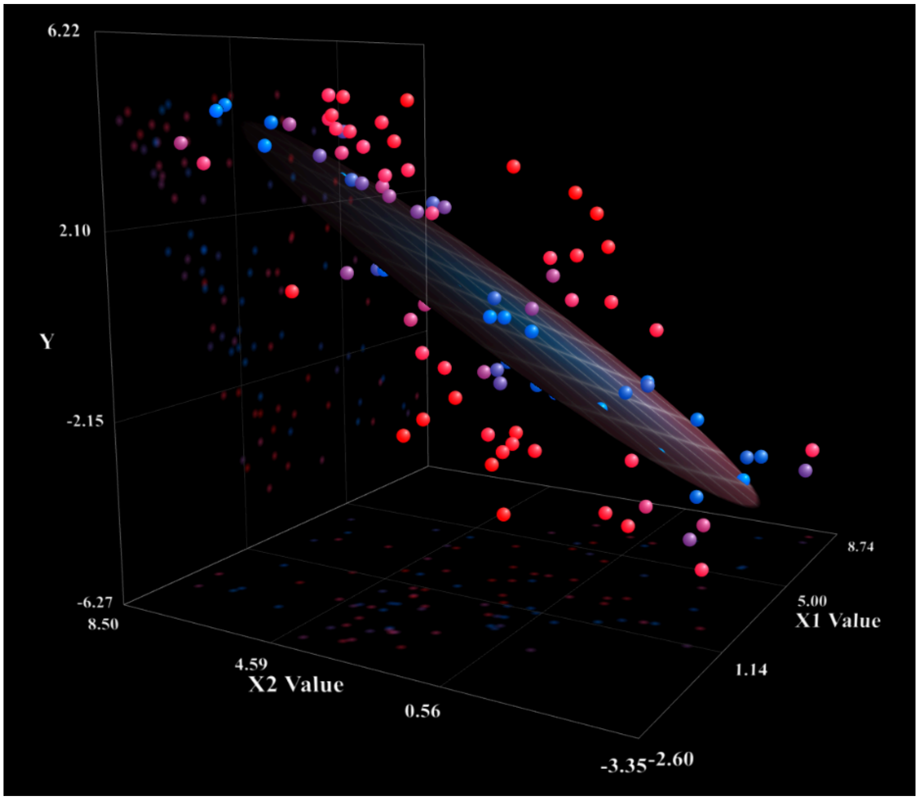


Specifically, we add a ω (weight) to the error term that will be smaller as the number of years gets bigger. Ie. if there is expected to be more variance, we will weight that term lower. Otherwise WLS works the same as OLS - we minimize the sum of all of the error terms (times the new weight term) squared.

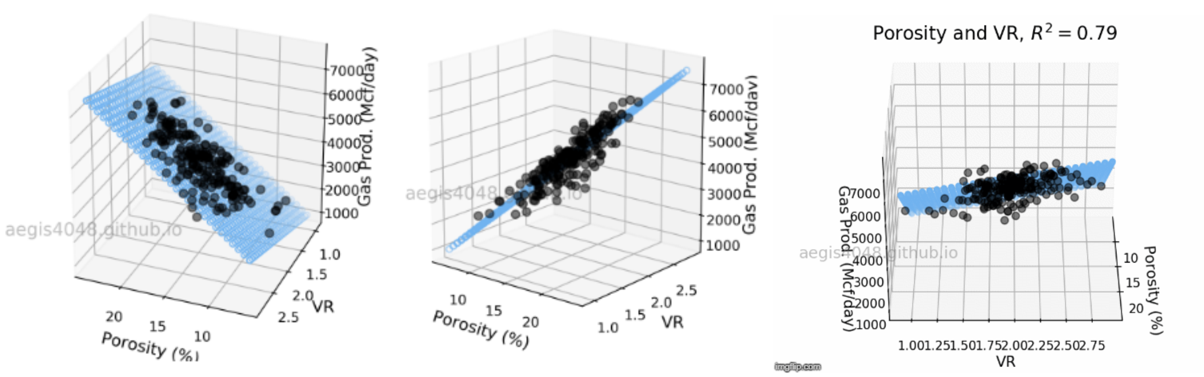
2 variate regression

Adding a second variable into the mix requires us to have a 3D drawing. In our example above, let's say we also wanted to investigate if the # of practices / week made a difference. So we would be looking at Awesomeness (vertical-axis) vs both # of years (x1) and # of practices / week (x2).

You would end up with a drawing like below. We would be looking for the best-fit **plane** that explained the data points and minimized the difference between each point and the plane, for all of the points at once. Below are some drawings from the internet showing examples of these kinds of plots. The best-fit plane takes the place of the best-fit line in the previous drawings.



Screen capture for the interactive 3D visualization tool at: https://miabellaai.net/regression.html



Plots from the blog post here: https://aegis4048.github.io/mutiple_linear_regression_and_visualization_in_python

The plane is constructed from 2 slopes, one for each of the axes you are examining. Linear regression solves for these slopes and so defines the best-fit plane.

With more than 2 variables, the math stays the same, but it gets harder to draw as more dimensions are added. What's important to feel is how we are looking for a set of linear slopes (eg. a line for 1 variable, a plane for 2 variables, etc.) that minimize the error between the calculated slopes and the actual data points.

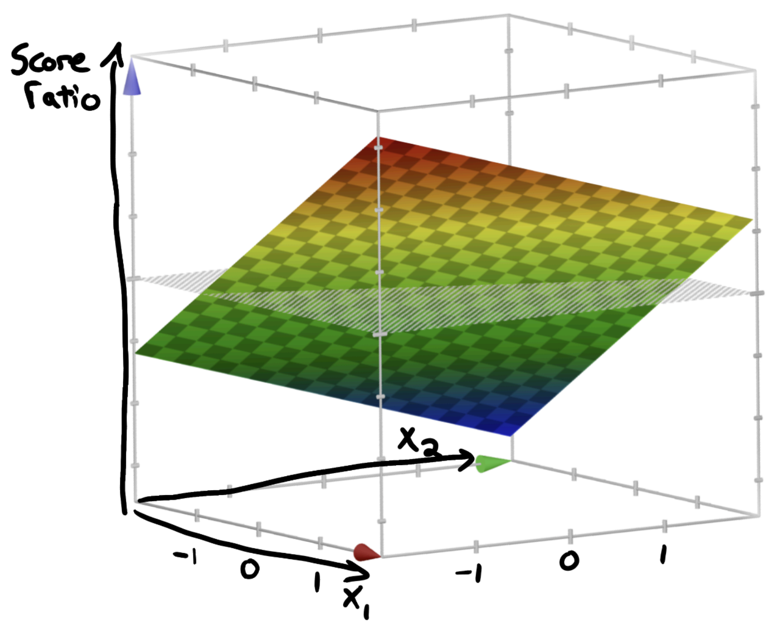
2 variate regression for rankings - Team A and B

When it comes to calculating rankings, we need to take into account all of the teams in the region. For 100 teams, this would be a 100-D drawing!

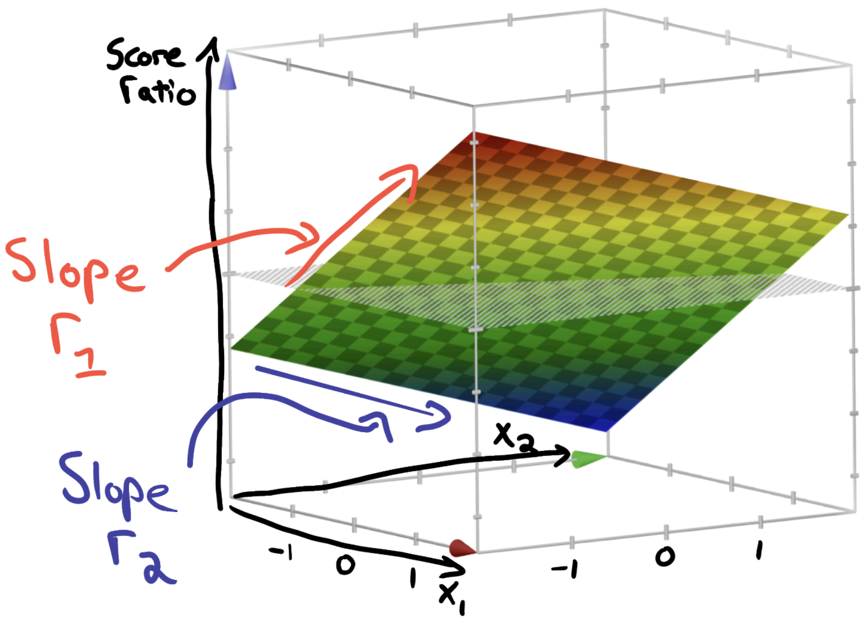
- Let's start easy and pretend there are only two teams in the region: Team A and B
- Let's consider only one single game
- We can draw this in a 3D graph (actually 2D but we use perspective to make it look 3D)

To calculate rankings, we are going to use Massy's handy trick (described above) by setting all the x values to 0 for teams not in the game which will reduce our drawing to only 2 horizontal axes. Then, for team 1 and 2, we only care about one single point on the graph: x1 = 1 and x2 = -1 and y = score ratio.

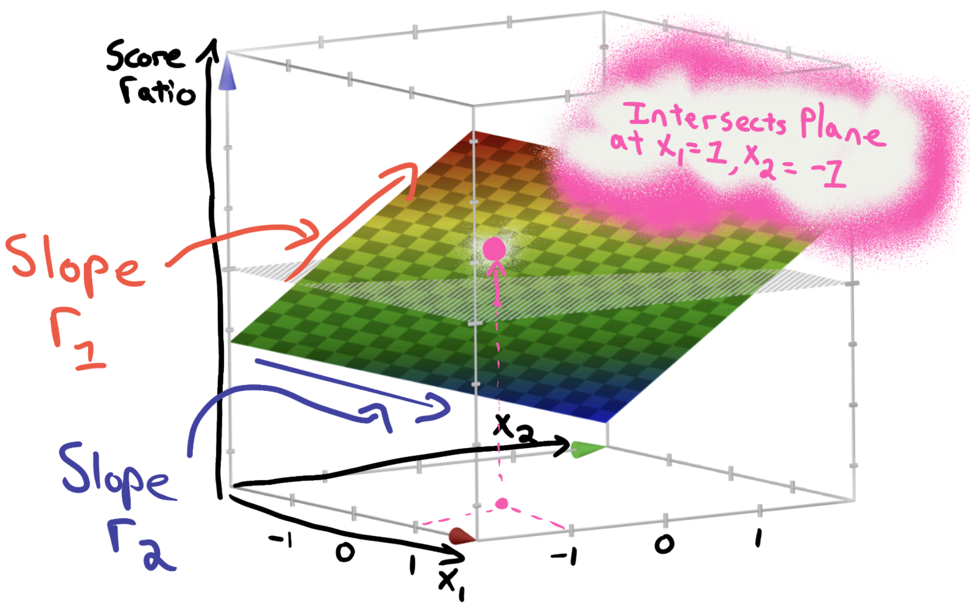
The y variable (score ratio) will only depend on the strength of those two teams, shown on the 2 horizontal variables, x1 and x2.



*The slope of the lines along x1 and x2 are the ln(rank) of the two teams. They make up a **plane** in 3D space. If 2 teams were exactly equal, this plane would be flat like a board lying on the ground. As teams are more different in rank, the board tilts up on a 3D diagonal.*



Linear regression will solve for the slopes of the 2 components of this plane.



In our setup, we only care about 1 location on the plane per game: where x1 = 1 and x2 = -1.
At this exact point, the plane will exactly intersect the ***game's score ratio****.*

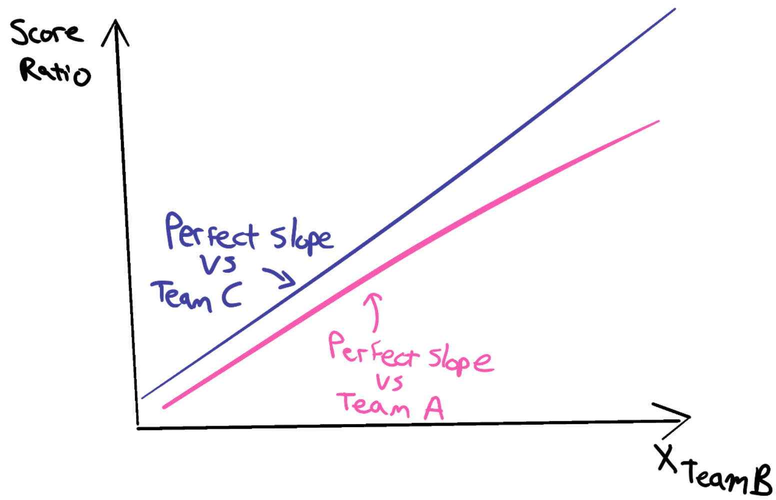
If we only cared about finding the RP for two teams based on one game, we'd have a perfect result. The ranking points would correspond perfectly to the slopes that created the plane that intersected the game score ratio value at x1 = 1 and x2 = -1.

2 variate regression for rankings - Team B and C

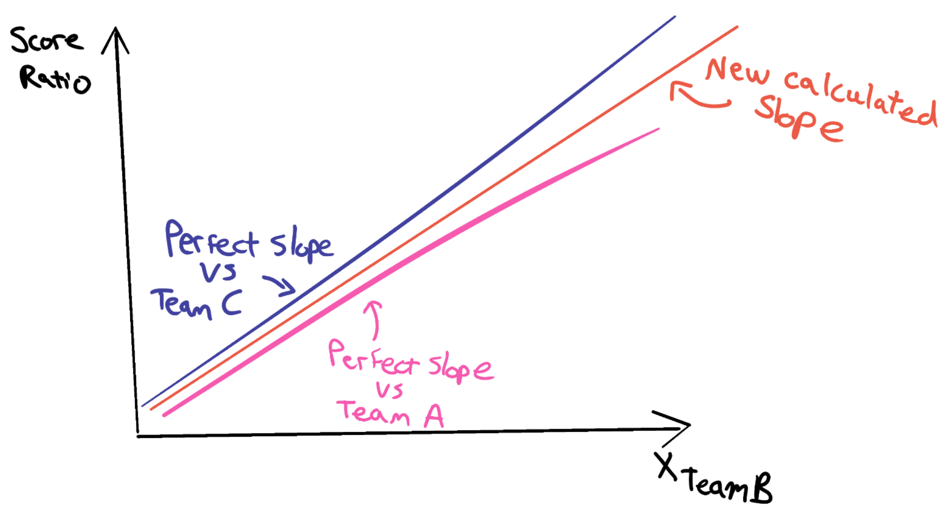
In the last drawing, there was only one game with two teams so there was no error. We could find slopes for the plane (ie. rankings for the team) that perfectly matched the game score. This will not be possible to do perfectly with more teams and games involved.

Let's imagine another game happens between Team B and a new team C. This will create a new plane like the one above but with different slopes for each team.

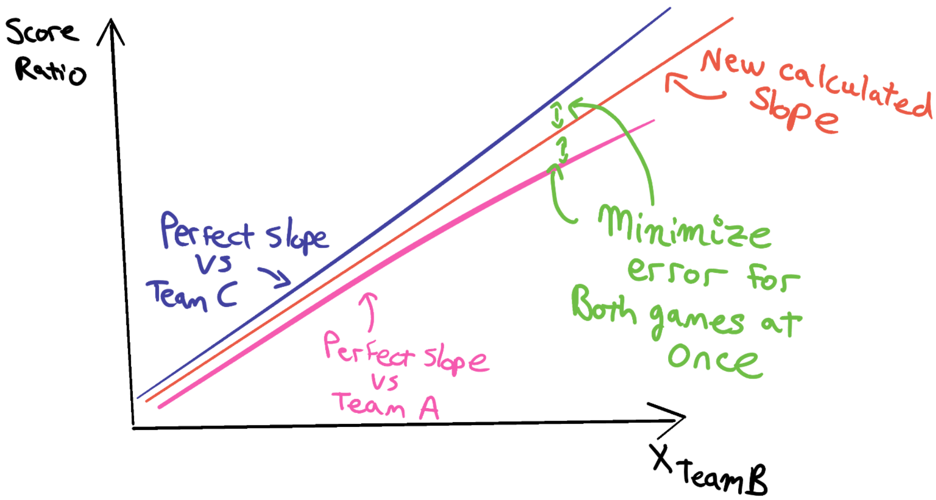
However, the perfect slope for Team B in the game against Team A will be different from the perfect slope for Team B in the new game against Team C. Picture these two slopes co-existing along the team b axis.



Team B has played two games. The perfect slope for each of these games is different. These (perfectly straight) lines are the "side" of the plane for each team in the 3D diagrams above.



We need a single rank for Team B. It will be some new, approximate slope that we calculate. This means the plane for Team B in its two graphs will not perfectly intersect the actual game score ratios like before.



*We calculate the new slope in such a way that we **minimize the errors** between the planes created with this slope and actual game score ratios.*

See if you are able to visualise two of those plane diagrams existing at the same time, and see how you need to solve for the slope of Team B in both games *at the same time* by getting the planes to be as close as possible to the game score ratios, even though there will be some error.

Extending to all games and all teams

Now try to imagine a plane diagram existing for every game played in the region. The proposed algorithm tries to find just one slope per team that minimizes the distance between every resulting plane and every real game score ratio, all at once.

It takes a multi-dimensional brain to overlay all of those planes on top of each other, but if you can get a sense of how over correcting for one team could make the overall system less accurate for the others and how everything needs to be solved together to minimize the error for all teams at once, you can get a feel for how it all works.

Lastly, remember we weigh outlier games over cap less than other games, so they will not “pull” the planes toward their score ratio as much as other games.

Appendix B: Evaluation of algorithm

MEAL

To evaluate if the proposed algorithm is “better”, we need to agree on a good way to measure accuracy. Accuracy can also be seen as measuring the “error” between predicted game outcomes and real results.

For team rankings, we don’t care what the absolute score of a game is as much as we care about the score ratio and the ratio between two teams rankings. Eg. our algorithms do not try to predict a game score of 200 to 100, but rather that one team will score twice as many points as the other.

Because we are dealing with ratios, we cannot average additive error measurements directly - like if we averaged percentage error from predicted ratios to game ratios. Instead we need to convert the ratios from multiplicative space into additive space using the **log** of the ratios.

There are a number of ways to measure error. See this Wikipedia article and the “Indicators of relative change” table for a few.

To evaluate our algorithms we use the Mean Error of Absolute Logs (MEAL). (This is a slightly forced anagram of the exact same measure: Mean Absolute Log Error).

$$MEAL = average\left(\left| ln\left(\frac{predicted\_ratio}{actual\_ratio}\right) \right| \right)$$

Calculating MEAL:

- For each game, calculate $ln\left(\frac{predicted\_ratio}{actual\_ratio}\right)$, this is the “Log Error”
- Take the absolute value
- This gives you the absolute log error for that single game
- Take the arithmetic mean of all games in a period of time / region you are interested in
    - sum of all absolute log errors / number of games

When you have the MEAL, you can convert back to percentage error by doing e^{MEAL} - 1.
Example:

- Game 1 : predicted ratio: 2:1, actual ratio 1.8:1
- Game 2 : predicted ratio 3:1, actual ratio 3.7:1
- Absolute Log Error for Game 1: $\left|ln\left(\frac{2}{1.8}\right)\right|$ = 0.105
- Absolute Log Error for Game 2: $\left|ln\left(\frac{3}{3.7}\right)\right|$ = 0.210
- MEAL = $\frac{0.105 + 0.210}{2}$ = 0.1575
- Percentage error = $e^{0.1575}$ - 1 = 1.170 - 1 = 17%

Accuracy of 2023 algorithm vs Proposed algorithm

	% Error 2023 algorithm (smaller is better)								% Error Proposed algorithm (smaller is better)							
month	Eur	L Am	NA NE	NA S	NA W	Oc	GUR	Total	Eur	L Am	NA NE	NA S	NA W	Oc	GUR	Total
2023-01	53.73%	-	-	-	-	-	-	53.73%	53.73%	-	-	-	-	-	-	53.73%
2023-02	55.66%	-	-	43.45%	8.30%	-	-	48.39%	53.94%	-	-	43.45%	8.30%	-	168.33%	61.44%
2023-03	66.44%	-	87.06%	97.39%	75.45%	290.35%	-	86.86%	75.64%	-	87.06%	98.58%	75.45%	290.35%	-	90.07%
2023-04	83.64%	-	92.78%	241.58%	128.04%	-	301.33%	112.36%	81.00%	-	91.11%	215.02%	114.24%	-	170.82%	103.20%
2023-05	97.41%	-	84.04%	124.13%	151.45%	-	253.22%	112.19%	78.56%	-	66.28%	86.99%	63.04%	-	129.42%	76.65%
2023-06	66.34%	-	109.01%	109.32%	90.96%	55.19%	49.74%	87.14%	57.55%	-	81.48%	94.11%	80.39%	55.19%	45.49%	72.31%
2023-07	68.85%	-	137.88%	57.69%	87.97%	-	13.49%	90.81%	87.96%	-	106.44%	45.72%	64.97%	-	23.58%	71.23%
2023-08	88.66%	-	106.57%	76.88%	294.34%	-	61.77%	107.82%	124.19%	-	81.80%	75.64%	222.58%	-	44.76%	88.23%
2023-09	124.27%	-	85.14%	72.58%	103.18%	63.11%	81.61%	88.87%	91.19%	-	66.09%	62.99%	74.91%	29.60%	50.97%	65.73%
2023-10	72.51%	192.07%	97.63%	60.42%	82.02%	218.77%	98.94%	85.68%	62.00%	152.50%	80.25%	56.14%	65.03%	260.24%	82.65%	78.46%
2023-11	47.26%	117.42%	60.44%	69.81%	67.04%	333.14%	50.82%	58.43%	35.38%	95.81%	49.37%	13.54%	62.53%	320.15%	31.60%	46.47%
2023-12	143.52%	49.70%	-	-	-	-	104.95%	65.28%	78.76%	82.65%	-	-	-	-	217.56%	89.96%
2024-01	79.05%	-	-	28.52%	132.97%	-	-	77.31%	74.13%	-	-	49.25%	132.97%	-	-	77.57%
2024-02	45.28%	-	23.59%	-	66.27%	-	-	46.72%	60.38%	-	20.32%	-	54.83%	-	-	55.25%
2024-03	44.21%	7.92%	59.70%	53.57%	81.40%	105.41%	-	61.01%	44.20%	8.56%	57.66%	66.26%	79.05%	123.89%	-	64.75%
2024-04	40.23%	82.54%	79.87%	101.47%	67.95%	-	68.28%	69.64%	42.32%	73.71%	65.17%	92.90%	62.25%	-	35.74%	58.61%
2024-05	95.45%	8.75%	79.37%	126.95%	159.33%	-	-	97.64%	72.33%	11.53%	59.49%	83.80%	124.57%	-	-	72.91%
2024-06	73.43%	-	60.04%	94.10%	59.76%	49.59%	-	67.05%	67.89%	-	57.43%	68.46%	64.32%	76.84%	96.27%	65.59%

	% Error 2023 algorithm (smaller is better)								% Error Proposed algorithm (smaller is better)							
month	**Eur**	**L Am**	**NA NE**	**NA S**	**NA W**	**Oc**	**GUR**	**Total**	**Eur**	**L Am**	**NA NE**	**NA S**	**NA W**	**Oc**	**GUR**	**Total**
2024-07	55.33%	-	76.76%	140.11%	-	-	-	90.77%	46.60%	-	69.76%	82.36%	-	-	-	69.30%
2024-08	88.15%	121.31%	82.27%	56.29%	70.83%	-	309.66%	78.50%	40.73%	142.73%	72.09%	62.12%	70.46%	-	41.69%	64.44%
2024-09	51.08%	-	109.77%	67.51%	104.30%	-	86.04%	93.46%	51.44%	-	116.39%	26.43%	71.40%	-	39.14%	70.53%
2024-10	56.35%	3.30%	94.38%	123.19%	112.40%	54.49%	104.16%	84.21%	53.38%	0.95%	65.52%	73.56%	71.07%	18.55%	53.90%	59.77%
2024-11	72.97%	13.06%	87.70%	-	108.25%	-	62.52%	80.09%	77.49%	51.04%	56.66%	-	84.63%	-	56.66%	72.52%
2024-12	67.27%	118.17%	-	-	-	-	-	72.28%	38.99%	122.15%	-	-	-	-	-	46.42%
2025-01	80.39%	-	-	-	-	-	-	80.39%	136.78%	-	-	-	-	-	-	136.78%
2025-02	98.50%	-	80.04%	151.68%	53.40%	-	-	100.58%	87.46%	-	53.02%	49.70%	44.47%	-	55.98%	75.39%
2025-03	51.04%	-	70.57%	77.22%	88.65%	140.83%	88.21%	71.73%	50.30%	-	69.03%	87.67%	74.52%	56.32%	45.64%	66.11%
total	67.56%	58.09%	84.71%	88.77%	93.31%	87.72%	87.86%	81.74%	61.30%	88.30%	71.49%	74.95%	74.89%	92.69%	55.81%	69.65%

Sample ranking

This is the actual April 1, 2025 ranking (left) compared with how it would look if the proposed algorithm had been used since the start of 2023 (right).

Jump to: Europe, Latin America, NA Northeast, NA South, NA West, Oceania, GUR

Europe

April 2025 ranking - Europe - 2023 algorithm		
1	Crime City A	484.87
2	Rainy City A	448.96
3	Toulouse	331.99
4	Paris AllStars	283.39
5	LDN Brawling	269.55
6	Nantes Duch.es	256.16
7	Antwerp Love	255.63
8	Tiger Bay	231.63
9	Stockholm	196.78
10	Helsinki A	186.46
11	Goteborg A	163.61
12	Barcelona A	146.82
13	Bear City	136.13
14	Dublin	132.36
15	Lomme	132.31
16	SAM	111.16
17	Namur A	106.58
18	Madrid A	88.7
19	Vienna	76.26
20	Kallio	75.12
21	Oulu	71.53
22	Valencia	70.99
23	Zurich	68.03

April 2025 ranking - Europe - new algorithm		
1	Crime City A	527.16
2	Toulouse	453.61
3	Rainy City A	418.19
4	Paris AllStars	357.25
5	LDN Brawling	317.15
6	Nantes Duch.es	288.77
7	Antwerp Love	251.69
8	Helsinki A	220.30
9	Tiger Bay	208.58
10	Goteborg A	194.53
11	Barcelona A	190.60
12	Stockholm	187.96
13	Lomme	171.04
14	Dublin	155.95
15	Bear City	139.88
16	Namur A	122.37
17	SAM	119.79
18	Vienna	100.71
19	Madrid A	97.65
20	Valencia	96.74
21	Auver'Niaks	86.85
22	Kallio	84.46
23	Oulu	82.96

April 2025 ranking - Europe - 2023 algorithm		
24	Mexico City	67.16
25	Rainy Reckon	60.3
26	Cres Lattes	56.74
27	Auver'Niaks	55.94
28	Caen	55.14
29	Newcastle UK	54.69
30	La Boucherie	54.44
31	Lisbon	51.51
32	St. Pauli	51.06
33	Auld Reekie A	50.22
34	Norrköping	49.65
35	Prague	45.77
36	Lyon	44.76
37	Tampere	44.04
38	Brussels	43.51
39	Norfolk	43.23
40	Birmingham A	39
41	Oslo	38.86
42	Leeds A	38.68
43	Nantes Divine	38.54
44	Rotterdam	38.25
45	Dresden	36.61
46	Liverpool	36.08
47	Birmingham B	35.14
48	Orléans	34.23
49	LDN Saints	34.07
50	Brest	33.51
51	Harpies	32.22
52	Wiltshire	31.24
53	Lutece	29.5

April 2025 ranking - Europe - new algorithm		
24	Mexico City	82.19
25	La Boucherie	79.39
26	Zurich	76.35
27	Caen	74.83
28	Norfolk	72.02
29	Auld Reekie A	69.71
30	St. Pauli	68.93
31	Cres Lattes	68.74
32	Prague	67.12
33	Leeds A	66.51
34	Norrköping	64.81
35	Lisbon	64.57
36	Rotterdam	62.82
37	Rainy Reckon	61.41
38	Ldn Batter C	59.92
39	RuhrPott	59.75
40	Dresden	58.79
41	Lyon	57.05
42	Brest	55.52
43	Oslo	55.23
44	Newcastle UK	53.15
45	Wiltshire	52.78
46	Birmingham A	51.64
47	Orléans	51.12
48	LDN Saints	49.61
49	Bristol	49.41
50	Tampere	48.93
51	Brussels	46.73
52	Liverpool	45.08
53	Nantes Divine	43.97

April 2025 ranking - Europe - 2023 algorithm		
54	Ldn Batter C	29.42
55	Bristol	29.33
56	Rebellion	28.85
57	Dundee	28.75
58	RuhrPott	28.66
59	Manchester	27.68
60	Helsinki Bees	27.65
61	Rennes	24.38
62	Copenhagen A	24.25
63	Aalborg	22.8
64	Bordeaux	20.83
65	Prague City	19.97
66	Brighton	19.55
67	Hamburg	18.17
68	Kaiserslautern	18
69	Paris Brkfast	17.25
70	Nidaros	15.44
71	Cologne	15
72	Glasgow	14.2
73	Regensburg	14.03
74	Anguanas	13.31
75	Sheffield	13.27
76	Auld Reekie B	12.29
77	Dirty River	12.27
78	Golden City	11.99
79	Oxford	11.98
80	Iceland	11.58
81	Kent	11.45
82	Goteborg B	11.44
83	Crime City B	11.08

April 2025 ranking - Europe - new algorithm		
54	Harpies	40.90
55	Helsinki Bees	40.43
56	Dundee	39.65
57	Rennes	37.99
58	Rebellion	37.68
59	Auld Reekie B	35.72
60	Aalborg	34.43
61	Paris Brkfast	32.79
62	Copenhagen A	30.83
63	Glasgow	27.39
64	Anguanas	27.11
65	Cologne	26.38
66	Bordeaux	26.11
67	Dirty River	23.83
68	À Coruña	23.70
69	Kaiserslautern	23.68
70	Sheffield	22.25
71	Hamburg	21.51
72	Brighton	20.86
73	Kent	20.75
74	Oxford	19.87
75	Nidaros	19.66
76	Crime City B	19.62
77	Manchester	19.60
78	Dom City	19.18
79	Goteborg B	18.63
80	Karlsruhe	17.74
81	Birmingham B	17.57
82	Lutece	16.48
83	Golden City	16.03

April 2025 ranking - Europe - 2023 algorithm		
84	Dom City	10.83
85	Eindhoven	9.54
86	À Coruña	8.16
87	Munich	7.75
88	Belfast	7.57
89	Bergen	6.73
90	Hulls Angels	6.26
91	Innsbruck	6.11
92	Karlsruhe	5.58
93	Barcelona B	3.72
94	Leeds B	3.7
95	London Rollers	3.67
96	Stuttgart	2.7
97	Antwerp Pack	2.62
98	Madrid B	2.44
99	Copenhagen B	2.06
100	Cape Town	0.14

April 2025 ranking - Europe - new algorithm		
84	Regensburg	15.28
85	Prague City	14.44
86	Munich	13.94
87	Antwerp Pack	13.67
88	Innsbruck	13.25
89	Stuttgart	13.14
90	Iceland	12.53
91	Bergen	10.79
92	Eindhoven	9.93
93	Hulls Angels	9.71
94	Leeds B	9.34
95	Belfast	7.38
96	London Rollers	5.81
97	Madrid B	4.97
98	Copenhagen B	4.82
99	Barcelona B	3.72
100	Cape Town	0.14

Latin America

April 2025 ranking - LATAM - 2023 algorithm		
1	2 x 4 Osom	406.63
2	Insurrectas	140.98
3	Colmena	138.07
4	Bone Breakers	105.53
5	Metropolitan	96.53
6	2 x 4 Pibxs	43.61
7	Tacones	43.24
8	Sailor City	42.17

April 2025 ranking - LATAM - new algorithm		
1	2 x 4 Osom	585.87
2	Colmena	193.06
3	Insurrectas	179.58
4	Bone Breakers	178.71
5	Metropolitan	177.69
6	Sailor City	142.69
7	2 x 4 Pibxs	80.48
8	Tacones	61.73

April 2025 ranking - LATAM - 2023 algorithm		
9	Atomic Bombs	32.62
10	Capital Rats	31.45
11	RnR Queens	10.93
12	Volcanicas	9.07

April 2025 ranking - LATAM - new algorithm		
9	Atomic Bombs	56.45
10	Capital Rats	55.67
11	Volcanicas	25.79
12	RnR Queens	19.48

NA Northeast

April 2025 ranking - NANE - 2023 algorithm		
1	Arch All Stars	3190.83
2	Montreal Skids	925.82
3	Gotham Al	743.94
4	Q City Furies	453.55
5	Detroit A	283.3
6	Minnesota A	282.52
7	Windy City A	275.4
8	Vette Cty Vix	252.5
9	Boston A	247.39
10	Steel Cty Hurt	245.9
11	Ohio	223.24
12	TC Thunder	199.56
13	Black Rose A	199.46
14	Ann Arbor A	192.45
15	CT All Stars	183.24
16	Montreal Sexpo	157.44
17	Penn Jersey	151.2
18	Arch Nemesis	150.83
19	Gotham Traitor	147.67
20	Windy City B	143.76
21	Team Ontario	111.06
22	Royal City	110
23	Naptown	98.23
24	N Star Novas	93.93
25	Brewcity A	89.04

April 2025 ranking - NANE - new algorithm		
1	Arch All Stars	3776.54
2	Montreal Skids	1087.78
3	Gotham Al	893.47
4	Minnesota A	424.85
5	Detroit A	400.67
6	Windy City A	366.54
7	Boston A	341.34
8	Q City Furies	289.02
9	Ann Arbor A	270.98
10	TC Thunder	259.30
11	Ohio	258.01
12	Black Rose A	232.95
13	Gotham Traitor	225.16
14	Arch Nemesis	208.92
15	CT All Stars	206.70
16	Montreal Sexpo	177.85
17	Steel Cty Hurt	174.04
18	Team Ontario	167.54
19	Penn Jersey	155.15
20	Windy City B	152.86
21	Vette Cty Vix	149.69
22	Royal City	121.26
23	Peterborough	120.17
24	N Star Novas	118.35
25	Grand Raggidy	115.17

April 2025 ranking - NANE - 2023 algorithm		
26	Grand Raggidy	88.57
27	Charlotte Maul	84.23
28	Ottawa Valley	76.89
29	Minnesota B	76.83
30	Muddy River	69.96
31	Akron All Star	69.23
32	Boston B	69.19
33	TC Lightning	64.32
34	Peterborough	60.4
35	Kzoo Killstars	59.96
36	Philly A	57.03
37	Gem City Reign	56.51
38	Circle City	56.31
39	Lehigh Valley	55.08
40	Detroit B	54.92
41	Atlantic RD	53.36
42	Quad City	50.75
43	Q City Sirens	50
44	Madison Dolls	48.75
45	N Star Lights	47.51
46	Black-n-Blue	46.79
47	Anchor City	46.63
48	Dirty Jersey	46.24
49	Small Town	45.66
50	Lakeshore	42.78
51	Maine	42.5
52	Flint	42.3
53	Lansing	42
54	Roc City Roc	41.43
55	Free St Suzies	41.21
56	Chicago-Style	38.26
57	Downriver	37.17
58	Quebec A	37.13

April 2025 ranking - NANE - new algorithm		
26	Kzoo Killstars	115.00
27	Gem City Reign	108.47
28	TC Lightning	108.22
29	Madison Dolls	102.75
30	Minnesota B	96.67
31	Atlantic RD	94.40
32	Brewcity A	93.15
33	Boston B	92.75
34	Akron All Star	84.68
35	Quebec A	83.05
36	Lakeshore	82.05
37	Lehigh Valley	81.78
38	Dirty Jersey	81.43
39	Q City Sirens	81.42
40	Circle City	80.05
41	Muddy River	78.81
42	Detroit B	77.39
43	Anchor City	76.65
44	Philly A	76.20
45	Charlotte Maul	76.05
46	Flint	75.05
47	Naptown	74.45
48	Ottawa Valley	69.50
49	Quad City	69.38
50	Twin State	62.50
51	Roc City Roc	61.94
52	Maine	59.35
53	DC	57.89
54	Small Town	55.83
55	Free St Suzies	50.70
56	Lansing	48.52
57	Chicago-Style	48.48
58	Burning Rvr A	46.17

April 2025 ranking - NANE - 2023 algorithm		
59	Twin State	36.42
60	Steel Cty Beam	35.96
61	Burning Rvr A	35.94
62	Fargo	35.35
63	BuxMont Sirens	35.24
64	South Shore	33.84
65	Cincinnati	31.5
66	Ktcky Rock St	30.88
67	Windy City C	29.57
68	Madison Herd	27.45
69	Fog City	26.67
70	Marquette	24.59
71	DC	23.9
72	Ghost Fleet	22.87
73	CoMo	22.78
74	Fox Cities	22.27
75	Ithaca	21.9
76	Boston C	21.62
77	Reading	20.72
78	Rockford Rage	19.92
79	Quebec B	19.43
80	Traverse City	19.13
81	Aurora 88s	18.72
82	Toronto	18.65
83	Green Mountain	18.01
84	Hammer City	17.61
85	Mass Attack	17.41
86	Bay State	17.11
87	Schuykill	17.09
88	Aroostook	16.97
89	Confluence	16.29
90	Wilkes-Barre	15.98
91	Salt City	15.64

April 2025 ranking - NANE - new algorithm		
59	CoMo	46.11
60	Fargo	44.13
61	Downriver	42.63
62	Confluence	40.00
63	Fox Cities	39.79
64	Ktcky Rock St	38.63
65	Cincinnati	38.62
66	BuxMont Sirens	37.36
67	Black-n-Blue	37.34
68	Mass Attack	35.60
69	Hammer City	34.87
70	Aroostook	34.61
71	Cornfed	34.28
72	Madison Herd	33.87
73	South Shore	32.56
74	Toronto	31.82
75	Traverse City	31.81
76	Fog City	30.04
77	Ithaca	29.57
78	Boston C	29.51
79	Marquette	28.80
80	Black Rose G&P	28.59
81	Windy City C	27.74
82	Ghost Fleet	27.40
83	Harrisbg Knock	27.12
84	Hellions	25.79
85	S Delaware	25.12
86	Reading	24.43
87	Salt City	23.83
88	Old Cap City	23.62
89	Steel Cty Beam	23.50
90	Wilkes-Barre	23.46
91	N Star Lights	23.00

April 2025 ranking - NANE - 2023 algorithm		
92	Hellions	15.63
93	State College	15.15
94	Hogtown	14.96
95	Old Cap City	14.8
96	Black Rose G&P	14.13
97	Brewcity B	14.03
98	CT Brutals	13.8
99	S Delaware	13.08
100	Chippewa	13
101	Harrisbg Knock	12.7
102	Harrisbg Fall	12.52
103	Dutchland	12.08
104	Demolition	11.99
105	Renegade	11.69
106	South Bend	11.6
107	Lafayette	11.5
108	Mid-State	11.09
109	Kingston Rogue	11
110	Dominion	10.74
111	Erie	10.73
112	BuxMont Valk	10.3
113	New Hampshire	10.08
114	Garden State	9.86
115	NOVA	9.68
116	Susquehanna	9.6
117	Maine Old Port	9.55
118	Enchanted	9.41
119	Purple Pain	8.9
120	Burning HazMat	8.8
121	Fredericksburg	8.18
122	Prairieland	7.72
123	Cornfed	7.63
124	Youngstown	7.42

April 2025 ranking - NANE - new algorithm		
92	Bay State	22.49
93	Hogtown	21.89
94	CT Brutals	21.85
95	Rockford Rage	19.89
96	Schuykill	19.41
97	Dutchland	19.37
98	Brewcity B	18.91
99	301 Dames	18.49
100	Demolition	18.39
101	Chippewa	18.24
102	State College	17.84
103	Quebec B	17.14
104	South Bend	16.17
105	NOVA	15.90
106	Green Mountain	15.35
107	Hartford	15.19
108	BuxMont Valk	14.75
109	Prairieland	14.73
110	New Hampshire	14.67
111	Gem City Fem	14.65
112	Harrisbg Fall	14.05
113	Kingston Rogue	13.98
114	Renegade	13.85
115	Purple Pain	13.49
116	Garden State	13.20
117	Rocktown	13.10
118	Aurora 88s	12.97
119	Vette Cty Ven	12.78
120	Mid-State	12.70
121	Enchanted	12.45
122	Youngstown	12.02
123	Dominion	11.94
124	Long Island	11.84

April 2025 ranking - NANE - 2023 algorithm		
125	Hartford	7.16
126	301 Dames	7.04
127	Diamond State	6.98
128	Rocktown	6.45
129	Durham	5.97
130	Ktcky Indie R	5.68
131	Keweenaw	5.13
132	Roc City B	5.06
133	Gem City Fem	4.88
134	Philly B	4.78
135	Long Island	3.95
136	Rock Coast	3.86
137	Morgantown	3.77
138	Ohio Valley	3.45
139	Akron Rowdy	3.32
140	Vette Cty Ven	1.65

April 2025 ranking - NANE - new algorithm		
125	Susquehanna	11.42
126	Erie	11.05
127	Fredericksburg	10.31
128	Durham	9.76
129	Lafayette	9.06
130	Keweenaw	8.66
131	Burning HazMat	8.50
132	Maine Old Port	8.44
133	Akron Rowdy	8.38
134	Diamond State	7.91
135	Philly B	7.24
136	Rock Coast	7.08
137	Ktcky Indie R	6.73
138	Roc City B	6.25
139	Ohio Valley	5.71
140	Morgantown	4.22

NA South

April 2025 ranking - NA South - 2023 algorithm		
1	Atlanta DSD	621.18
2	New Jax City	553.82
3	Texecutioners	264.78
4	Red Stick A	235.74
5	Rockin Hits	211.32
6	Chattanooga A	163.51
7	Columbia	153.55
8	Discordias	147.76
9	Team Charlotte	104.72
10	Tampa Tantrums	99.95
11	KCRW All Stars	99.94
12	Twistr Victory	98.95
13	Dub City	91.5

April 2025 ranking - NA South - new algorithm		
1	New Jax City	1149.73
2	Atlanta DSD	710.37
3	Texecutioners	543.65
4	Red Stick A	499.19
5	Discordias	344.30
6	Tampa Tantrums	314.51
7	Chattanooga A	311.50
8	Columbia	294.26
9	Rockin Hits	271.31
10	Dallas Army	220.35
11	Twistr Victory	177.17
12	Team Charlotte	159.28
13	KCRW All Stars	139.32

April 2025 ranking - NA South - 2023 algorithm		
14	Appalachian	83.64
15	Capital City	74.45
16	Dallas Army	73.5
17	Greenville	72.81
18	Rvr City Riot	68.4
19	Chattanooga B	65.38
20	No Coast	63.7
21	Assassin A	62.15
22	Rome	61.32
23	Bradentucky	57.62
24	Blue Rdge YAll	57.21
25	Orlando Ozone	56.14
26	Atlanta Bs	54.53
27	Tragic City	51.51
28	Big Easy	47.65
29	Fort Myers	45.97
30	Memphis A	44.8
31	Twin Valleys	43.23
32	TXRG Chainsaws	42.29
33	Charlotte Bad	37.4
34	Panhandle B	37.27
35	Houston	36.03
36	Orlando Block	33.05
37	Lowcountry A	32.25
38	Nashville	30.53
39	North Texas	25.73
40	Carolina A	25.57
41	Soul City	24.82
42	Gold Coast	24.61
43	Jax Rat Pack	24.35
44	Natural State	24.35
45	Columbia Soda	18.52
46	Panhandle A	17.97

April 2025 ranking - NA South - new algorithm		
14	Assassin A	137.53
15	Greenville	126.76
16	Capital City	115.63
17	Blue Rdge YAll	111.89
18	Orlando Ozone	111.21
19	Dub City	109.18
20	Atlanta Bs	107.48
21	Houston	99.95
22	No Coast	97.27
23	Rvr City Riot	89.90
24	Twin Valleys	87.10
25	Bradentucky	87.09
26	TXRG Chainsaws	85.69
27	Big Easy	76.40
28	Appalachian	74.14
29	Chattanooga B	69.69
30	Fort Myers	69.12
31	Tragic City	67.93
32	Rome	65.36
33	Gold Coast	57.15
34	Memphis A	54.32
35	Nashville	53.37
36	Carolina A	50.17
37	Lowcountry A	49.84
38	Jax Rat Pack	41.92
39	Natural State	40.63
40	North Texas	39.96
41	Springfield	34.06
42	Fayetteville	30.92
43	Panhandle A	29.59
44	Classic City	27.93
45	Alamo City	27.90
46	Orlando Block	27.54

April 2025 ranking - NA South - 2023 algorithm		
47	Rock Town	16.8
48	Springfield	16.75
49	Gainesville	16.45
50	Tampa Bruise	14.12
51	LCHR Betties	13.21
52	Alamo City	12.09
53	Fayetteville	11.81
54	West Florida	11.63
55	Hard Knox A	11.6
56	Druid City	11.53
57	Classic City	11.24
58	Rocket City	11.23
59	580	10.87
60	Dallas Battal	10.62
61	Red Stick Cap	9.81
62	Peach State	8.79
63	Yellow Rose	8.21
64	Roughneck	8.13
65	Conroe	7.77
66	Tallahassee	7.75
67	Blue Rdge Retr	7.71
68	Relentless	6.67
69	Cape Fear	6.11
70	Twistr Tornado	5.38
71	Memphis B	5.16
72	RC River Rats	5.14
73	Roe City	4.73
74	Rockin Tracks	4.45
75	Little City	3.79
76	Greensboro	3.6
77	Cape Girardeau	3.5
78	Savannah	3.19
79	Muscogee	2.99

April 2025 ranking - NA South - new algorithm		
47	Tampa Bruise	26.18
48	Columbia Soda	25.86
49	Rock Town	24.48
50	Gainesville	22.46
51	Rocket City	22.37
52	Dallas Battal	22.28
53	Conroe	21.70
54	Greensboro	19.26
55	Cape Fear	18.92
56	Red Stick Cap	18.89
57	Druid City	17.52
58	Hard Knox A	17.44
59	LCHR Betties	17.35
60	580	17.30
61	Panhandle B	17.09
62	Charlotte Bad	15.46
63	Blue Rdge Retr	14.62
64	Tallahassee	14.18
65	Yellow Rose	13.63
66	Rockin Tracks	13.58
67	RC River Rats	13.46
68	Savannah	12.75
69	West Florida	12.39
70	Peach State	12.32
71	Roughneck	12.32
72	Muscogee	11.58
73	Soul City	11.14
74	West Texas	11.04
75	Memphis B	9.99
76	Relentless	9.81
77	Little City	8.62
78	Twistr Tornado	8.18
79	Roe City	7.70

April 2025 ranking - NA South - 2023 algorithm		
80	Richland Cnty	2.79
81	West Texas	1.63
82	Cap Cty TTown	1.19

April 2025 ranking - NA South - new algorithm		
80	Cape Girardeau	6.79
81	Richland Cnty	5.06
82	Cap Cty TTown	1.81

NA West

April 2025 ranking - NA West -2023 algorithm		
1	Rose WoJ	2569.37
2	Denver MHC	1756.82
3	Rose AoA	942.09
4	Calgary	765.09
5	Supernovas UV	614.57
6	Angel Scarlets	459.12
7	Groms Legacy	395.69
8	Santa Cruz A	354.64
9	Happy Valley	224.01
10	AZ All Stars	214.5
11	Rat City	203.25
12	Denver BA	198.01
13	Jet City	196.14
14	GVRDA Summit	123.65
15	Sac MaulStars	117.68
16	SoCal Kraken	102.15
17	Baja A	97.8
18	Humboldt Redwd	94
19	Casa Grande A	92.49
20	Wasatch	90.57
21	Angel Queens	89.87
22	Rage City	84.73
23	V Town A	84.19
24	Bakersfield	84.11
25	Coyote	82.71
26	Team Montana	79.66
27	Elev All Stars	71.09

April 2025 ranking - NA West - new algorithm		
1	Rose WoJ	3660.25
2	Denver MHC	2050.29
3	Rose AoA	1283.70
4	Angel Scarlets	827.40
5	Groms Legacy	622.57
6	Supernovas UV	576.27
7	Calgary	559.37
8	Santa Cruz A	458.52
9	Happy Valley	398.00
10	Rat City	296.03
11	AZ All Stars	291.61
12	Denver BA	269.40
13	Jet City	233.41
14	Baja A	185.73
15	Casa Grande A	149.93
16	SoCal Kraken	141.42
17	Team Montana	136.23
18	Rage City	135.31
19	GVRDA Summit	130.83
20	Cherry City	124.87
21	Nuclear Free	117.37
22	Bakersfield	113.40
23	Rocky Mtn 5280	100.87
24	Angel Queens	99.28
25	Sac MaulStars	97.33
26	Bay Area	96.81
27	Saskatoon	89.91

April 2025 ranking - NA West -2023 algorithm		
28	Cherry City	70.36
29	Bay Area	63.87
30	Outlaws	62.79
31	Gorge	60.07
32	N AZ Outlaws	58.16
33	Rocky Mtn 5280	57.31
34	Treasure V AS	57.17
35	Saskatoon	55.74
36	Arizona Rising	41.43
37	Nuclear Free	40.75
38	Angel Shots	39.86
39	FoCo	38.49
40	Rat City B	36.61
41	Pile O'Bones	36.57
42	Naughty Pines	35.3
43	Dockyard	35.06
44	Inland Empire	33.8
45	Los Alamos	32.46
46	Monterey Bay	32
47	Bouldr Phoenix	31.93
48	Bisman Bomb	30.96
49	Supernovas BB	29.43
50	West Coast TKO	28.45
51	Faultline	28.41
52	Sin City Ace	28.32
53	Eves	27.33
54	El Paso TxPist	27.26
55	S Cruz Hellcat	26.82
56	Bellingham	25.84
57	PPRD All-Stars	25.5
58	TM Big Sky	24.96
59	Denver Standby	24.92
60	San Fern OMGs	24.62

April 2025 ranking - NA West - new algorithm		
28	Treasure V AS	87.58
29	V Town A	85.37
30	N AZ Outlaws	85.30
31	Coyote	84.68
32	Rat City B	73.44
33	Humboldt Redwd	69.59
34	Gorge	68.17
35	Elev All Stars	64.31
36	Dockyard	60.15
37	Bellingham	59.29
38	Outlaws	58.80
39	FoCo	56.95
40	Eves	54.90
41	Bouldr Phoenix	54.51
42	Arizona Rising	54.11
43	West Coast TKO	53.86
44	Wasatch	52.97
45	S Cruz Hellcat	51.00
46	PPRD Slamazons	48.30
47	Angel Shots	43.46
48	Supernovas BB	41.98
49	El Paso TxPist	41.03
50	PPRD All-Stars	38.90
51	Denver Standby	38.17
52	TM Big Sky	37.00
53	Naughty Pines	36.53
54	Ventura Dolls	36.35
55	Sin City Ace	34.99
56	Pile O'Bones	34.56
57	N AZ Whiskey	32.42
58	Monterey Bay	32.26
59	San Fern OMGs	31.82
60	Faultline	31.35

April 2025 ranking - NA West -2023 algorithm		
61	PPRD Slamazons	20.81
62	High Altitude	20.44
63	N AZ Whiskey	20.02
64	Wine Town	18.98
65	Baja B	18.14
66	Sierra All Str	17.32
67	Sick Town	15.33
68	SO Derby	15.09
69	Ventura Dolls	14.11
70	Bouldr Bolters	13.07
71	Lava City	12.14
72	Sac Bruin Tro	11.97
73	Humboldt Force	11.46
74	Central Coast	11.19
75	El Paso PistWp	11.09
76	North Bay	10.96
77	Lilac City	9.89
78	Terminal City	9.78
79	Peninsula	9.58
80	Shasta	9.42
81	GVRDA Cascades	9.33
82	Tucson	9.31
83	Casa Grande B	9.15
84	SoCal Cuttle	8.78
85	Nor Cal	8.45
86	V Town B	8.2
87	Pacific	7.44
88	Sin City Beats	7.33
89	Sierra Demons	5.89
90	Sac Kodiak	4.44
91	Treasure V BRR	3.12
92	West Sound	3.06
93	Carquinez	1.62

April 2025 ranking - NA West - new algorithm		
61	Inland Empire	31.19
62	Sierra All Str	30.97
63	Wine Town	30.68
64	Bisman Bomb	29.26
65	Los Alamos	26.33
66	Casa Grande B	25.30
67	High Altitude	24.97
68	Tucson	23.86
69	Baja B	23.84
70	SO Derby	20.48
71	Bouldr Bolters	20.07
72	Humboldt Force	18.57
73	North Bay	18.30
74	Sin City Beats	17.43
75	Shasta	16.86
76	Peninsula	16.08
77	Central Coast	15.40
78	Sac Bruin Tro	15.02
79	Lilac City	14.21
80	SoCal Cuttle	12.95
81	Sac Kodiak	11.35
82	V Town B	11.10
83	El Paso PistWp	11.09
84	Lava City	9.71
85	Sierra Demons	9.70
86	Nor Cal	8.87
87	Pacific	8.85
88	Treasure V BRR	5.79
89	West Sound	4.77
90	Carquinez	2.16
91	Sick Town	1.37
92	Terminal City	0.87
93	GVRDA Cascades	0.83

Oceania

April 2025 ranking - Oceania - 2023 algorithm		
1	VRDL All Stars	1030.23
2	Brisbane Punk	280.68
3	Adelaide Ads	222.15
4	Perth Evils	205.77
5	Sun St Swarm	175.86
6	Brisbane Red	136.05
7	Sydney	120.64
8	Pirate City	91.46
9	Richter City	55.45
10	South Sea A	52.3
11	Convict City	50.05
12	Canberra	48.27
13	VRDL Thunder	44.48
14	West Aust RD	35.82
15	Newcastle Aus	24.19
16	Swamp City	23.97
17	Perth Bees	23.62
18	Radelaide	19.07
19	Sun State Bees	17.58
20	East Vic	15.76
21	Dunedin	14.69
22	South Sea Ban	11.44
23	Auckland	8.35

April 2025 ranking - Oceania - new algorithm		
1	VRDL All Stars	751.82
2	Adelaide Ads	172.73
3	Brisbane Punk	155.09
4	Perth Evils	122.74
5	Sun St Swarm	113.30
6	Pirate City	77.68
7	Sydney	58.39
8	Richter City	54.18
9	Brisbane Red	50.39
10	Canberra	44.01
11	VRDL Thunder	36.11
12	Convict City	34.47
13	South Sea A	33.06
14	Newcastle Aus	29.09
15	West Aust RD	26.33
16	Swamp City	25.98
17	Radelaide	17.26
18	East Vic	15.46
19	Dunedin	14.35
20	Sun State Bees	14.20
21	South Sea Ban	13.95
22	Perth Bees	10.63
23	Auckland	7.56

GUR

April 2025 ranking - GUR - 2023 algorithm		
1	Rose WoJ	2386.04
2	Arch All Stars	1897.17
3	Denver MHC	1332.18
4	VRDL All Stars	971.63
5	Montreal Skids	864.48

April 2025 ranking - GUR - new algorithm		
1	Rose WoJ	3789.97
2	Arch All Stars	2622.79
3	Denver MHC	2032.16
4	VRDL All Stars	1817.11
5	Montreal Skids	1302.57

April 2025 ranking - GUR - 2023 algorithm		
6	Crime City A	825.05
7	Angel Scarlets	767.09
8	Gotham Al	705.07
9	New Jax City	501.29
10	Toulouse	492.82
11	Red Stick A	492.22
12	Rose AoA	448.28
13	N Star Novas	411.07
14	Sac MaulStars	379
15	CT All Stars	357.07
16	Texecutioners	324.4
17	Santa Cruz A	322.52
18	Minnesota A	280.4
19	Atlanta DSD	279.7
20	Adelaide Ads	275.66
21	Windy City A	251.41
22	Nantes Duch.es	247.5
23	Rainy City A	219.34
24	Chattanooga A	194.31
25	Grand Raggidy	166.37
26	S Cruz Hellcat	166.28
27	Detroit A	163.41
28	Montreal Sexpo	161.03
29	Denver BA	159.19
30	Minnesota B	156.63
31	Ohio	156.26
32	North Texas	148.54
33	Black Rose A	137.32
34	Supernovas UV	136.18
35	Atlanta Bs	125.33

April 2025 ranking - GUR - new algorithm		
6	Crime City A	1175.96
7	Angel Scarlets	1088.03
8	Rose AoA	1065.03
9	Gotham Al	974.90
10	Toulouse	815.70
11	Rainy City A	764.92
12	Supernovas UV	698.14
13	New Jax City	688.77
14	Minnesota A	578.05
15	Atlanta DSD	498.14
16	Calgary	481.42
17	Nantes Duch.es	468.92
18	Red Stick A	422.96
19	Texecutioners	380.93
20	Detroit A	377.85
21	Windy City A	377.00
22	Tiger Bay	376.47
23	Santa Cruz A	373.62
24	Happy Valley	325.62
25	Adelaide Ads	309.55
26	Chattanooga A	253.23
27	AZ All Stars	250.74
28	Black Rose A	246.41
29	Ohio	240.45
30	Denver BA	229.60
31	Dallas Army	223.09
32	CT All Stars	214.78
33	Gotham Traitor	209.61
34	Arch Nemesis	177.71
35	Steel Cty Hurt	163.23

April 2025 ranking - GUR - 2023 algorithm		
36	Denver Standby	118.14
37	No Coast	112.88
38	Brighton	100.6
39	Calgary	99.25
40	Happy Valley	98.54
41	Gotham Traitor	96.26
42	Dallas Army	95.03
43	Philly A	90.94
44	Saskatoon	81.77
45	Bay Area	81.26
46	Windy City B	81.23
47	Steel Cty Hurt	74.99
48	Blue Rdge YAll	71.57
49	AZ All Stars	69.86
50	Charlotte Maul	69.51
51	Twistr Victory	67.32
52	Tiger Bay	66.32
53	Rocky Mtn 5280	59.37
54	Team Montana	59.26
55	Arch Nemesis	38.58
56	PPRD All-Stars	38.24
57	Twin Valleys	37.85
58	Rvr City Riot	34.1
59	Zurich	31.44
60	TXRG Chainsaws	29.89
61	Glasgow	28.96
62	Greenville	28.51
63	Iceland	26.85
64	KCRW All Stars	24.45
65	Ithaca	24.33

April 2025 ranking - GUR - new algorithm		
36	Montreal Sexpo	149.48
37	Twistr Victory	148.99
38	Windy City B	134.79
39	KCRW All Stars	134.01
40	N Star Novas	125.84
41	Sac MaulStars	122.38
42	Team Montana	121.35
43	Grand Raggidy	115.28
44	No Coast	114.82
45	Greenville	109.40
46	Rocky Mtn 5280	106.30
47	Minnesota B	104.50
48	Zurich	102.71
49	Blue Rdge YAll	94.20
50	Atlanta Bs	94.03
51	V Town A	92.27
52	Charlotte Maul	81.87
53	Twin Valleys	80.77
54	Rvr City Riot	78.98
55	TXRG Chainsaws	76.44
56	Bay Area	75.76
57	Philly A	75.17
58	Saskatoon	68.59
59	Detroit B	68.19
60	S Cruz Hellcat	56.16
61	Lansing	42.30
62	Supernovas BB	41.89
63	Denver Standby	41.17
64	Glasgow	39.56
65	North Texas	39.18

April 2025 ranking - GUR - 2023 algorithm		
66	Ktcky Rock St	24.06
67	Supernovas BB	22.92
68	Lansing	22.51
69	V Town A	21.53
70	Faultline	19.81
71	Sac Bruin Tro	18.88
72	Traverse City	12.86
73	Detroit B	11.38
74	Ohio Valley	7.06
75	Philly B	5.91
76	Little City	4.51
77	Hard Knox A	4.29

April 2025 ranking - GUR - new algorithm		
66	PPRD All-Stars	39.15
67	Ktcky Rock St	37.90
68	Brighton	36.37
69	Faultline	31.00
70	Traverse City	29.65
71	Ithaca	29.58
72	Iceland	29.18
73	Hard Knox A	15.19
74	Sac Bruin Tro	14.88
75	Little City	7.44
76	Philly B	7.26
77	Ohio Valley	6.58