NB: As the total filesize of my data and project code exceeds Blackboard's upload limit, please note that it is publicly available on Github at URL `http://github.com/sverona/meleeWHR`. Partial replication instructions are available in the repository's readme file.

1 Background and problem description

Super Smash Bros. Melee, a fighting game originally released in 2001, has recently experienced a resurgence in competitive play. Major tournament series such as Genesis and Evolution regularly attract upwards of 1,000 entrants [1], a scale otherwise unheard of for decade-old games incapable of online play.

Melee It On Me (*MIOM*), the competitive community's primary governing body, produces annual ranking lists of the 100 most skilled players, established by panel vote. While the general accuracy of these lists is widely accepted, both the placement of individual players and the rankings' general methodology are highly debated within the community at large. There have been many attempts at using existing rating systems such as Elo and Glicko to generate comparable rankings, but few are still publicly maintained, partially due to the scattered nature of the available data. Further, these rankings (like their MIOM counterparts) are produced at infrequent intervals from aggregated resuls. Thus, since the scene lacks a formal competitive circuit, the task of ranking the top players attending an upcoming tournament (e.g., for seeding purposes) falls mainly on that tournament's organizers.

2 Objectives

The goals of this project were to

i. consolidate the available tournament data, dating as far back as 2003-4, into a publicly maintained dataset;
ii. use this dataset and a maximum-likelihood estimation method such as Whole-History Rating (*WHR*) [2] to reconstruct real-time ratings for the period comprising the earliest modern tournaments in 2004-5 to the present day;
iii. use D3.js [3] to visualize these time-series in a manner similar to [4].

Items (i) and (ii) were completed to some degree of satisfaction. Item (iii) was accomplished through Matplotlib (see appendix.) Visualization using D3.js remains a future goal (see Section 6.4.)

3 Overview of methodology and research question

The primary question of interest is to derive a stable measure of player skill from the sequence of match records. One method of doing so that has been adopted by other e-sports communities is TrueSkill [5], which assumes that player skill before any given match follows a Gaussian distribution. The probability of one player defeating another is then roughly approximated by the probability that a randomly sampled value from the former's distribution exceeds one from the latter's; this gives rise to the *Bradley-Terry model*

$$P_t(i > j) \approx \frac{\mu_{it}}{\mu_{it} + \mu_{jt}},$$

where μ_{it}, μ_{jt} are the means of players i and j's distributions at time t. The TrueSkill algorithm, like many others, performs maximum-likelihood estimation of these parameters using this assumption. One goal of this project is to adapt this algorithm slightly to model some of the peculiarities of *SSBM*'s competitive environment, as demonstrated, e.g., in [6].

The WHR algorithm differs from TrueSkill in that it performs MLE retroactively over the player's entire rating history (hence the name.) However, the mathematics is similar; [5] gives a whole-history extension of TrueSkill that, according to [2], produces similar results to WHR.

Ratings were interpolated using the following formula given in [2]; if the mean of a player's skill distribution at time t, μ_t, is to be interpolated from the values $\mu_{t_1} = \mu_1$ and $\mu_{t_2} = \mu_2$, then we have

$$\mu_t = \frac{\mu_1(t_2 - t) + \mu_2(t - t_1)}{t_2 - t_1}.$$

4 Data cleaning

The data consists primarily of match metadata from tournament brackets, as shown in the sample below at left. This data was sourced from Liquipedia [7][8], using a scraper written in Python, and cleaned and reformatted into JSON, as in the sample below at right. It contains the match data from a set between top-level players at the tournament Shine 2017.


```
|l1m3p1=S2J |l1m3p1flag=us |l1m3p1score=3
|l1m3p2=HugS |l1m3p2flag=us |l1m3p2score=1
|l1m3win=1
|l1m3p1char1=cf |l1m3p2char1=samus |l1m3p1stock1
    ↪ =0 |l1m3p2stock1=1 |l1m3win1=2 |
    ↪ l1m3stage1=Yoshi's Story
|l1m3p1char2=cf |l1m3p2char2=samus |l1m3p1stock2
    ↪ =1 |l1m3p2stock2=0 |l1m3win2=1 |
    ↪ l1m3stage2=Pokémon Stadium
|l1m3p1char3=cf |l1m3p2char3=samus |l1m3p1stock3
    ↪ =2 |l1m3p2stock3=0 |l1m3win3=1 |
    ↪ l1m3stage3=Yoshi's Story
|l1m3p1char4=cf |l1m3p2char4=samus |l1m3p1stock4
    ↪ =3 |l1m3p2stock4=0 |l1m3win4=1 |
    ↪ l1m3stage4=Yoshi's Story
|l1m3date=August 26, 2017
|l1m3details={{BracketMatchDetails|reddit=|
    ↪ comment=|vod=https://www.youtube.com/
    ↪ watch?v=7zTSvNM-E1c}}
```

```
"l1m3": {
    "date": "August 26, 2017",
    "details": {
        "comment": "",
        "reddit": "",
        "vod": "https://www.youtube.com/watch?
            ↪ v=7zTSvNM-E1c"
    },
    "p1": "S2J",
    "p1char1": "cf", "p1char2": "cf", "p1char3
        ↪ ": "cf", "p1char4": "cf",
    "p1flag": "us",
    "p1score": "3",
    "p1stock1": "0", "p1stock2": "1", "
        ↪ p1stock3": "2", "p1stock4": "3",

    "p2": "HugS",
    "p2char1": "samus", "p2char2": "samus", "
        ↪ p2char3": "samus", "p2char4": "
        ↪ samus",
    "p2flag": "us",
    "p2score": "1",
    "p2stock1": "1", "p2stock2": "0", "
        ↪ p2stock3": "0", "p2stock4": "0",

    "stage1": "Yoshi's Story", "stage2": "Pok\
        ↪ u00e9mon Stadium", "stage3": "Yoshi
        ↪ 's Story", "stage4": "Yoshi's Story
        ↪ ",

    "win": "1",
    "win1": "2", "win2": "1", "win3": "1", "
        ↪ win4": "1"
}
```


The resulting JSON data was sufficiently flexible to be input into the WHR algorithm. Further applications of this dataset may require the imposition of a relational schema.

4.1 Relevant source code

The raw bracket data is stored in the directory `brackets/`. Data formatted as Wikitext (above left) has the extension `*.wiki`, while data stored as JSON has the extension `*.wiki.json`.

The Liquipedia scraper is located at `scrape_brackets.py`; the Wikitext-to-JSON parser is located at `parse_wikitext.py`.

5 Results

The computed ratings are stored in a JSON file and plotted using Matplotlib (see the appendix.) The pertinent source code is located at `list_top_players.py`.

5.1 Evaluation

This section compares the results output by WHR at the end of each year from 2004 to 2016 with those compiled by MIOM (from 2013 to 2016) or by the RetroSSBMRank panel (from 2004 to 2012.) The algorithm's precision, recall, and F_1-score is evaluated for the top 10 (for Retro rankings) or top 25 (for MIOM rankings) players as evaluated by the foregoing source. For Retro rankings, if an honorable mention was predicted within the top 10, it was counted as one-half of a false positive. Detailed tables are included as an appendix.

Period	TP	FP	FN	Precision	Recall	F_1 score
2004	8	2	2	80%	80%	80%
2005	7	2.5	3	73.68%	70%	71.79%
2006	6	3.5	4	63.16%	60%	61.54%
2007	7	3	3	70%	70%	70%
2008	6	2.5	4	70.59%	60%	64.86%
2009	7	1.5	3	82.35%	70%	75.68%
2010	8	1.5	2	84.21%	80%	83.72%
2011	8	2.5	4	76.19%	66.67%	71.11%
2012	7	2.5	3	73.68%	70%	71.79%
2013	20	5	5	80%	80%	80%
2014 Summer	20	5	5	80%	80%	80%
2014	20	5	5	80%	80%	80%
2015 Summer	19	6	6	76%	76%	76%
2015	20	5	5	80%	80%	80%
2016	20	5	5	80%	80%	80%

The performance is consistently around 75 percent, except in 2006 and 2008. Explanations for these can be found in Section 6.1 below. During the MIOM years, the algorithm's false positives were repeatedly drawn from the same set of six to seven international and inactive players, which MIOM explicitly disconsidered due to a lack of pertinent data. Were these players discarded from the WHR rankings, precision would improve to as much as 92 percent (in 2014.)

These ratings accord with a loose overview of Melee history. Setting the above table's findings aside, the magnitude of the ratings attained by the "Five Gods" (Hungrybox, Armada, Mango, Mew2King, and PPMD) through the period around 2010 to 2015 provide a clear picture of their dominance over the competition; during this period, with few exceptions, one of the Five Gods won every event at which at least two were in attendance. Also visible are the player Ken's early dominance from approximately 2004 to 2006 and the rapid rise of the "godslayers" Leffen and Plup, the only two players to have defeated all Five Gods. The player Wobbles, who has defeated four of the five (all except Armada,) also makes a visible peak around 2012 to 2013.

6 Directions for further improvement

6.1 Better missing value interpolation

The primary shortcoming of this project is its total ignorance of tournaments for which the brackets have been lost to history, but for which the rank-order placement data survives. Many such events fall between 2003 and 2006, during the competitive scene's so-called "stone age" and "golden age." Both periods predated widespread use of tournament tracking software (brackets were kept on paper, etc.) This partially explains the lower performance in those years; the RetroSSBMRank panelists compiled those rankings using data not currently available to the algorithm.

Adding these results to the dataset will require some form of interpolation to approximate each player's path through the bracket. For example, the round in which each player was eliminated can be determined purely from the rank-order data. Working backward from this, Monte Carlo methods can be used to obtain an approximation of the mean strength of each bracket round. Then, each entrant's approximate bracket path can be represented by victories or losses against a "dummy" player of each round's approximate skill. This may bias the variance of the WHR estimates downward, leading to imprecise future estimates, but this inaccuracy is minor compared to the ones stemming from the current absence of this data.

6.2 Further data gathering and reconstruction

Many other events have bracket data that is either not publicly available or in a different format (e.g., XML documents generated by tournament software that have not been parsed and assimilated by Liquipedia.) Thus, there are several major tournament brackets, most prominently the 2007 tournament known as MELEEFC-Diamond, that can largely be reconstructed from available data. However, tracking this data down will require reaching out to those tournaments' organizers (and in some cases, entrants) individually, and as such entail a time commitment outside the scope of a semester project.

6.3 More robust data model

Although JSON is probably sufficient for most small-scale applications of this dataset, the current data model is the minimal viable one for this project. Refactoring to support interpolated brackets, unknown match data, implementation of further features such as stage and character choice, etc. may be of interest.

6.4 Visualization and web application

A plot of all players' ratings over time that has more interactive visual aids (e.g., highlighting of a moused-over time series,) will improve the usability of these results. I plan to implement this using D3.js. On a longer-term scale, I would like to transfer the data I have into a webapp that provides individual match data richer than any single current source.

6.5 Comparison with other ranking algorithms

It is possible that the performance of this algorithm is eclipsed by simpler Elo-based systems, contrary to the findings presented in [2]. However, the problems presented in Section 6.1 make an objective comparison difficult. Further, as WHR encapsulates many simpler Elo-based systems as special cases [2], this is an unlikely premise in any case.

References

[1] https://www.ssbwiki.com/List_of_largest_Smash_tournaments

[2] https://www.remi-coulom.fr/WHR/WHR.pdf

[3] https://d3js.org/

[4] https://www.youtube.com/watch?v=z2DHpW79w0Y

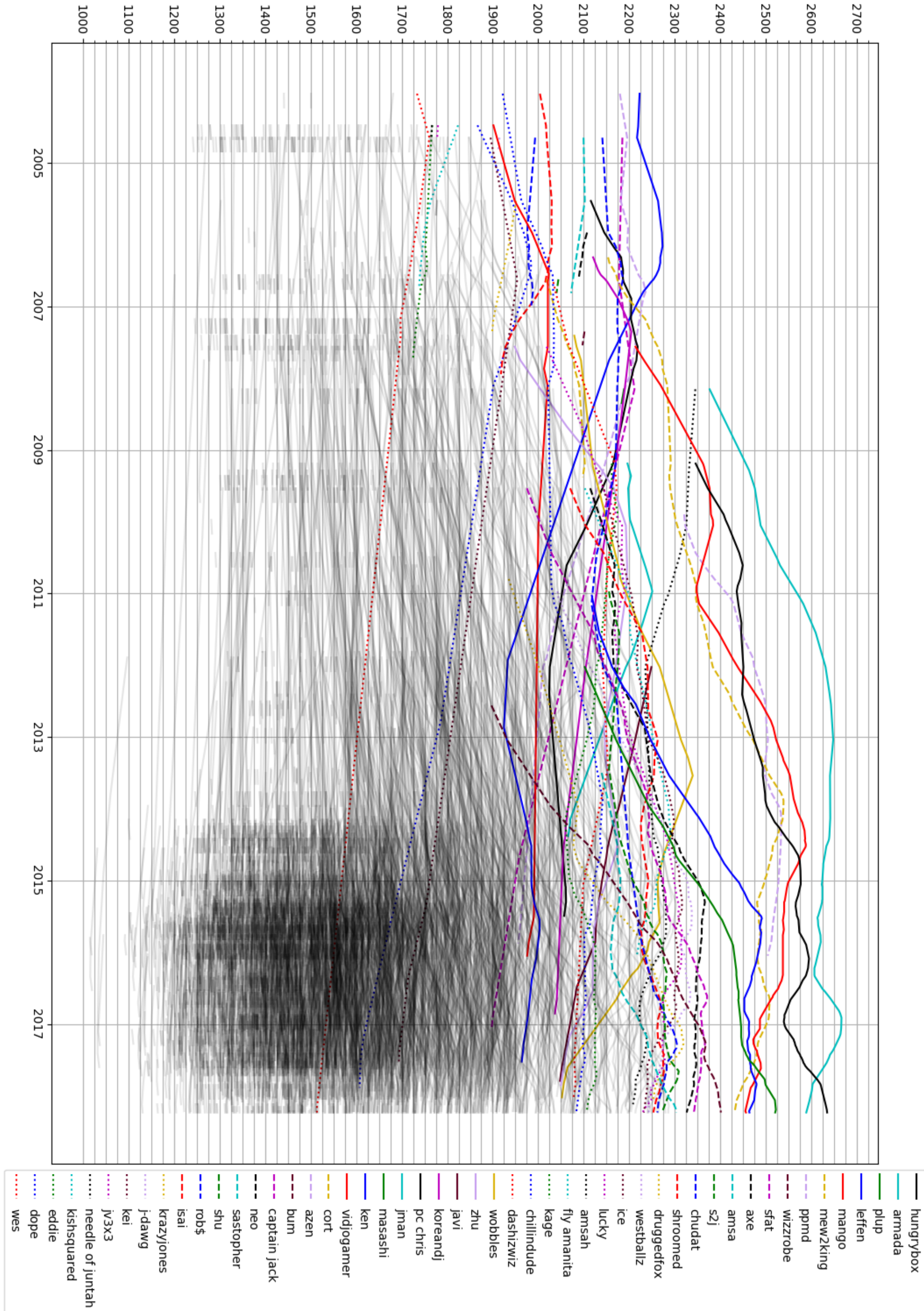
[5] https://papers.nips.cc/paper/3331-trueskill-through-time-revisiting-the-history-of-chess.pdf

[6] https://www.reddit.com/r/SSBM/comments/4pitia/an_objective_ranking_system_that_compensates_for/

[7] http://liquipedia.net/smash/Main_Page

[8] http://liquipedia.net/smash/index.php?title=Shine/2017/Melee/Singles_Bracket&action=edit&section=4

7 Time-series plot of data



8 RetroSSBMRank and Modern SSBMRank vs. WHR

Table 1: 2004

Player	RetroRank	WHR Rank
Ken	1	1
Captain Jack	2	3
Azen	3	2
Isai	4	6
ChuDat	5	4
Sastopher	6	5
Wes	7	NR
Rori	8	NR
Chillindude	9	8
Rob$	10	7
Vidjo	NR	9
J-Dawg	NR	10

Table 2: 2005

Player	RetroRank	WHR Rank
Ken	1	1
ChuDat	2	4
Isai	3	8
Azen	4	2
Vidjo	5	10
NEO	6	6
Chillindude	7	9
KrazyJones	8	13
Caveman	9	20
DieSuperFly	10	22
PC Chris	HM	5
Captain Jack	NR	3
Sastopher	NR	7

Table 3: 2006

Player	RetroRank	WHR Rank
Ken	1	2
Azen	2	1
PC Chris	3	4
ChuDat	4	7
KoreanDJ	5	6
Mew2King	6	3
Isai	7	19
Vidjo	8	15
Chillindude	9	14
DieSuperFly	10	22
NEO	HM	8
Captain Jack	NR	5
Sastopher	NR	9
DaShizWiz	NR	10

Table 4: 2007

Player	RetroRank	WHR Rank
Mew2King	1	1
Ken	2	8
KoreanDJ	3	6
PC Chris	4	4
ChuDat	5	7
Azen	6	5
Chillindude	7	16
Drephen	8	33
Cort	9	12
Mango	10	2
Captain Jack	NR	3
Wobbles	NR	9
DaShizWiz	NR	10

Table 5: 2008

Player	Retro Rank	WHR Rank
Mew2King	1	4
Mango	2	2
Cort	3	17
Azen	4	10
PC Chris	5	7
ChuDat	6	8
KoreanDJ	7	6
HugS	8	33
Ka-master	9	NR
Jman	10	NR
Armada	HM	1
Amsah	HM	3
Captain Jack	HM	5
Masashi	NR	9

Table 6: 2009

Player	Retro Rank	WHR Rank
Mango	1	3
Armada	2	1
Hungrybox	3	2
Mew2King	4	6
DaShizWiz	5	11
Jman	6	7
Zhu	7	8
Darkrain	8	33
PC Chris	9	22
PPMD	10	5
Amsah	HM	4
Lucky	HM	9
Kage	HM	10

Table 7: 2010

Player	RetroRank	WHR Rank
Hungrybox	1	2
Mango	2	4
Armada	3	1
Mew2King	4	5
PPMD	5	3
Jman	6	7
Amsah	7	6
KirbyKaze	8	22
Lucky	9	12
Fly Amanita	10	9
Zhu	HM	10
Ice	NR	8

Table 8: 2011 (top 12)

Player	RetroRank	WHR Rank
Armada	1	1
Mango	2	4
PPMD	3	2
Hungrybox	4	3
Mew2King	5	5
Lovage	6	30
Zhu	7	16
Fly Amanita	8	10
Shroomed	9	7
Wobbles	10	6
S2J	11	15
Axe	12	17
Amsah	HM	8
Ice	HM	9
Jman	HM	11
KirbyKaze	NR	12

Table 9: 2012

Player	RetroRank	WHR Rank
Armada	1	1
PPMD	2	3
Mango	3	2
Hungrybox	4	4
Mew2King	5	5
Wobbles	6	6
KirbyKaze	7	13
Zhu	8	29
ChuDat	9	22
Shroomed	10	7
Fly Amanita	HM	8
Leffen	NR	9
Ice	NR	10

Table 10: 2013

Player	SSBMRank	WHR Rank
Mango	1	2
Armada	2	1
Mew2King	3	3
PPMD	4	4
Hungrybox	5	5
Hax	6	22
Shroomed	7	19
Wobbles	8	7
KirbyKaze	9	16
SFAT	10	17
Axe	11	10
PewPewU	12	21
Ice	13	8
Leffen	14	6
Ryan Ford	15	40
Silent Wolf	16	14
Javi	17	27
Zhu	18	31
S2J	19	30
Lucky	20	11
Fly Amanita	21	9
ChuDat	22	24
Westballz	23	12
Taj	24	NR
Overtriforce	25	18
Amsah	NR	13
Plup	27	15
Gucci	65	20
Flash	NR	23
Fuzzyness	59	25

Table 11: 2014 Summer

Player	SSBMRank	WHR Rank
PPMD	1	4
Mango	2	2
Mew2King	3	5
Armada	4	1
Hungrybox	5	3
Leffen	6	6
Hax	7	17
Westballz	8	12
Fly Amanita	9	10
Shroomed	10	22
SFAT	11	18
aMSa	12	33
Ice	13	8
S2J	14	29
Colbol	15	24
KirbyKaze	16	21
Axe	17	7
PewPewU	18	14
Fiction	19	32
Silent Wolf	20	15
Zhu	21	30
Lucky	22	13
Plup	23	9
Javi	24	37
Overtriforce	25	19
Wobbles	NR	11
Amsah	NR	16
Gucci	NR	20
Flash	NR	23
Fuzzyness	NR	25

Table 12: 2014

Player	SSBMRank	WHR Rank
Mango	1	3
Armada	2	1
PPMD	3	4
Mew2King	4	5
Hungrybox	5	2
Leffen	6	6
Axe	7	7
Hax	8	18
Westballz	9	9
Colbol	10	24
Fly Amanita	11	17
Lucky	12	11
PewPewU	13	12
Shroomed	14	20
Silent Wolf	15	15
Plup	16	8
Fiction	17	35
S2J	18	27
Ice	19	10
SFAT	20	14
Zhu	21	41
aMSa	22	32
KirbyKaze	23	23
Nintendude	24	30
MacD	25	29
Amsah	NR	15
Wobbles	NR	16
Gucci	NR	19
Overtriforce	NR	22
Flash	NR	25

Table 13: 2015 Summer

Player	SSBMRank	WHR Rank
Armada	1	1
Leffen	2	6
Mango	3	3
PPMD	4	4
Hungrybox	5	2
Mew2King	6	5
Plup	7	7
Axe	8	8
Westballz	9	9
PewPewU	10	16
Shroomed	11	23
Lucky	12 (tie)	11
SFAT	12 (tie)	13
Silent Wolf	14	12
Hax	15	22
MacD	16	20
Ice	17	10
S2J	18	21
HugS	19	43
KirbyKaze	20	27
Fly Amanita	21	17
aMSa	22	38
Wizzrobe	23	30
Druggedfox	24	37
The Moon	25	39
Amsah	NR	14
Professor Pro	NR	15
Gucci	NR	17
Wobbles	NR	18
Trifasia	NR	24
Overtriforce	NR	25

Table 14: 2015

Player	SSBMRank	WHR Rank
Armada	1	1
Hungrybox	2	2
Leffen	3	5
Mango	4	3
Mew2King	5	6
PPMD	6	4
Plup	7	7
Westballz	8	11
Axe	9	8
Shroomed	10	26
Silent Wolf	11	13
Lucky	12	10
SFAT	13	9
PewPewU	14	19
MacD	15	22
S2J	16	14
Ice	17	12
Druggedfox	18	23
Hax	19	22
HugS	20	43
Colbol	21	24
Duck	22	27
Wizzrobe	23	30
aMSa	24	38
Nintendude	25	38
Gucci	NR	15
Amsah	NR	16
Professor Pro	NR	18
Wobbles	NR	20
Trifasia	NR	21

Table 15: 2016

Player	SSBMRank	WHR Rank
Armada	1	1
Hungrybox	2	2
Mango	3	4
Mew2King	4	3
Leffen	5	6
Plup	6	7
SFAT	7	8
Westballz	8	11
Axe	9	10
Shroomed	10	19
Swedish Delight	11	17
Wizzrobe	12	9
Ice	13	13
PewPewU	14	20
Duck	15	25
S2J	16	15
Nintendude	17	38
n0ne	18	27
Lucky	19	16
Silent Wolf	20	37
The Moon	21	21
ChuDat	22	14
Druggedfox	23	12
Professor Pro	24	26
Colbol	25	34
PPMD	NR	5
Rudolph	NR	18
Gucci	NR	22
KirbyKaze	NR	23
Trifasia	NR	24