Fantasy Football Weekly Report

Clay McLeod

November 4, 2014

Introduction

Hello! This is a completely automated Fantasy Football report produced by Clay McLeod. I'm using this as sort of an experiment to package together all of my fantasy football data analysis into one, easy to understand package. As I'm sure you can imagine, this system is pretty cutting edge so it's unlikely I will get everything formatted and explained correctly the first time. Continue to think of this report as being in it's experimental stage. I'm releasing it to get feedback from the community.

Updates

- Greatly improved DPS algorithm due to popular demand
- Added Rushing and Receiving Statistics category
- Please let me know how I can improve this system using my contact details below. This includes what metrics you would like to see!
- I really need help with spelling corrections! I'm kind of depending on crowdsourcing this as most of my time on the project is going into developing the system. Please let me know if you come across any spelling errors

Contact Information

- Reddit: http://reddit.com/u/clmcl
- Website: http://claymcleod.github.io/blog/

Tiered Visualizations

Motivation

Visualization of data is obviously very important. But often, as in the case of fantasy football, it can be crucial to making sense of data that normally very difficult to interpret. This post was inspired by the Fantasy Football Tier Visualiations performed by Boris Chen at the New York Times.

Visualizations

Many of you are familiar with the NYT visualizations referenced above. However, I don't believe the NYT's visualizations are capturing the full potential of this method. Therefore, I am developing my own methods of visualizing the data and posting them.

Differences

There are two main differences between these visualizations and the New York Times visualizations. First, my visualizations use the most current rankings whereas the New York Times visualizations appear to use data from August 21 (about a month ago). Second, my algorithm finds the most optimal number of tiers, while the New York Times visualizations force the algorithm to find 8 tiers. Hopefully you find these insightful.

Drive/Developer Projects/Python/pyffl/data/generated/tiered/qb.png

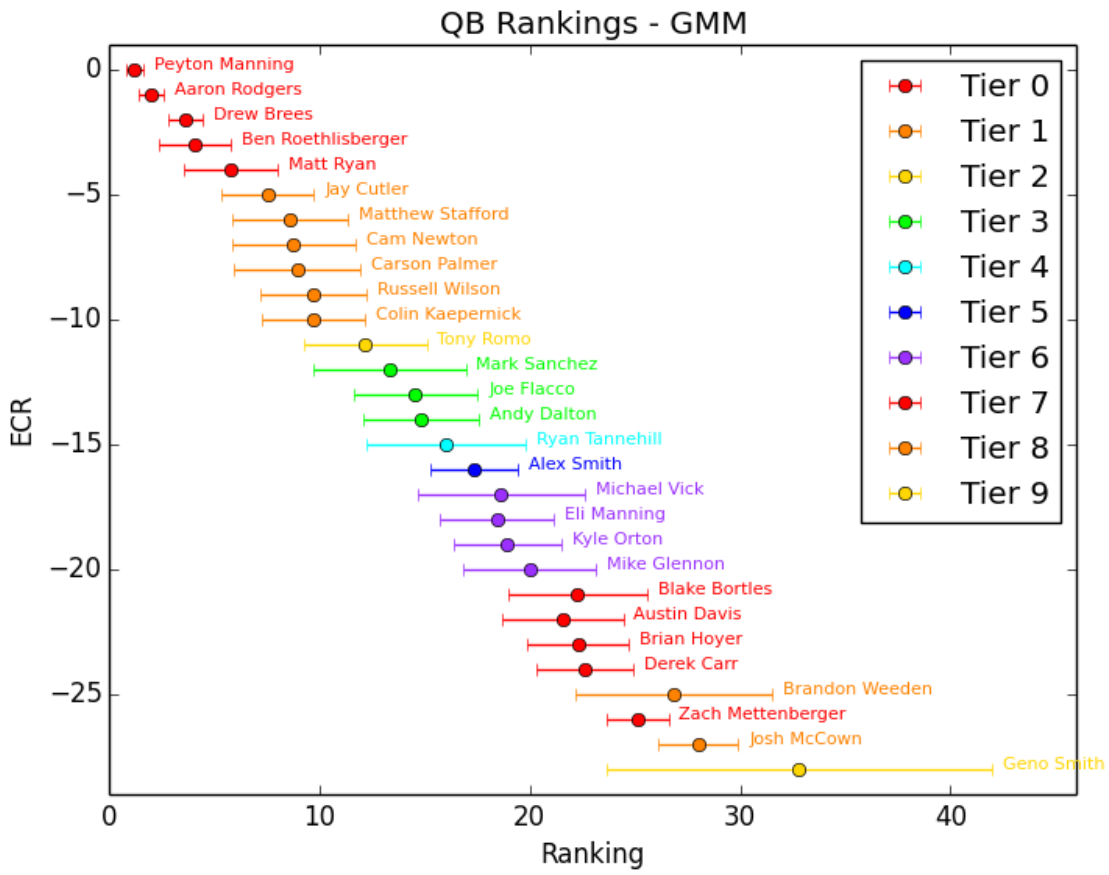

Figure 1: QB Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/rb.png

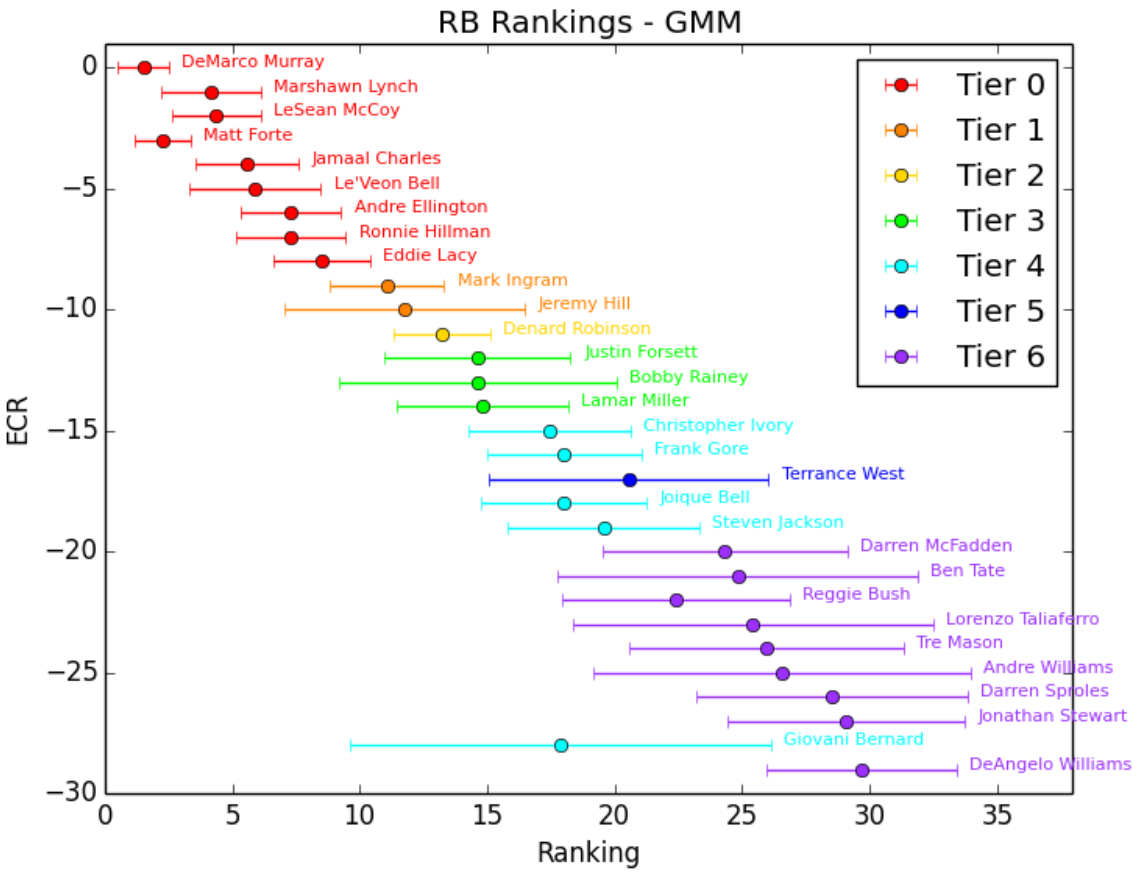

Figure 2: RB Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/wr.png

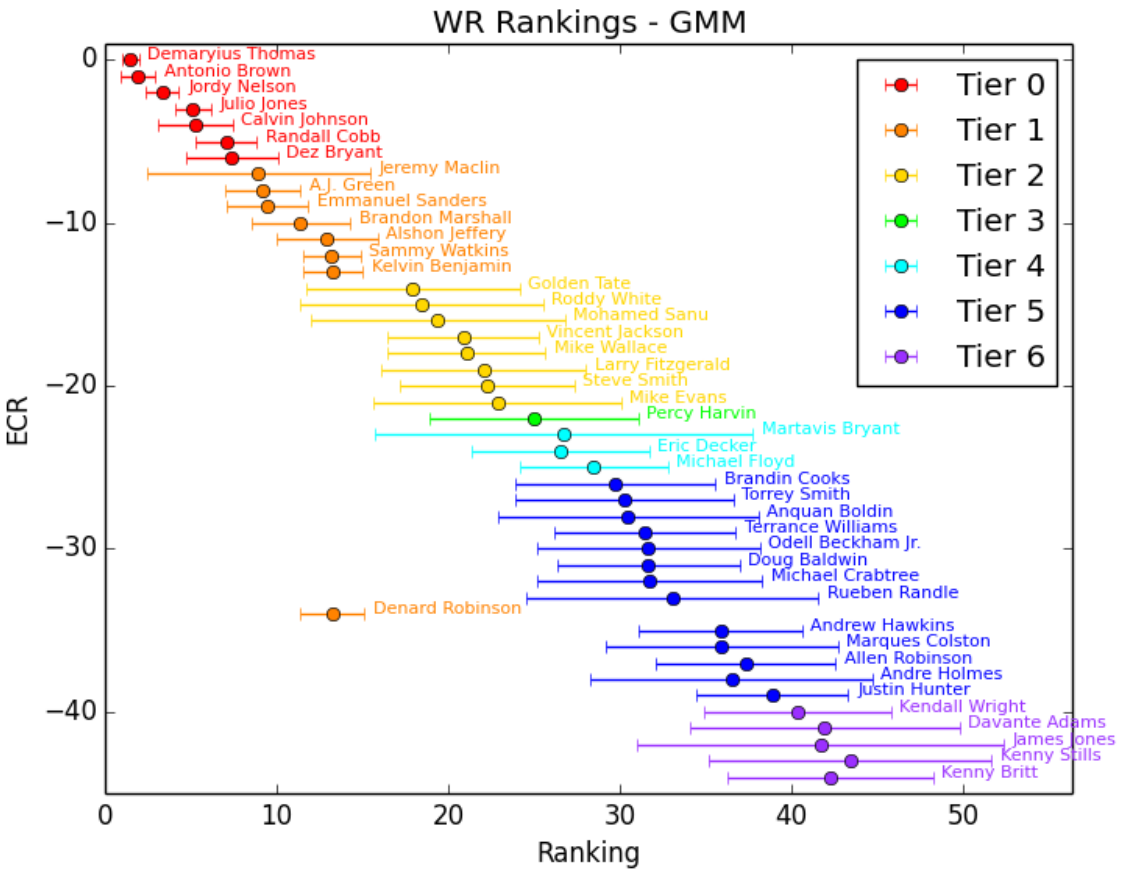

Figure 3: WR Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/flex.png

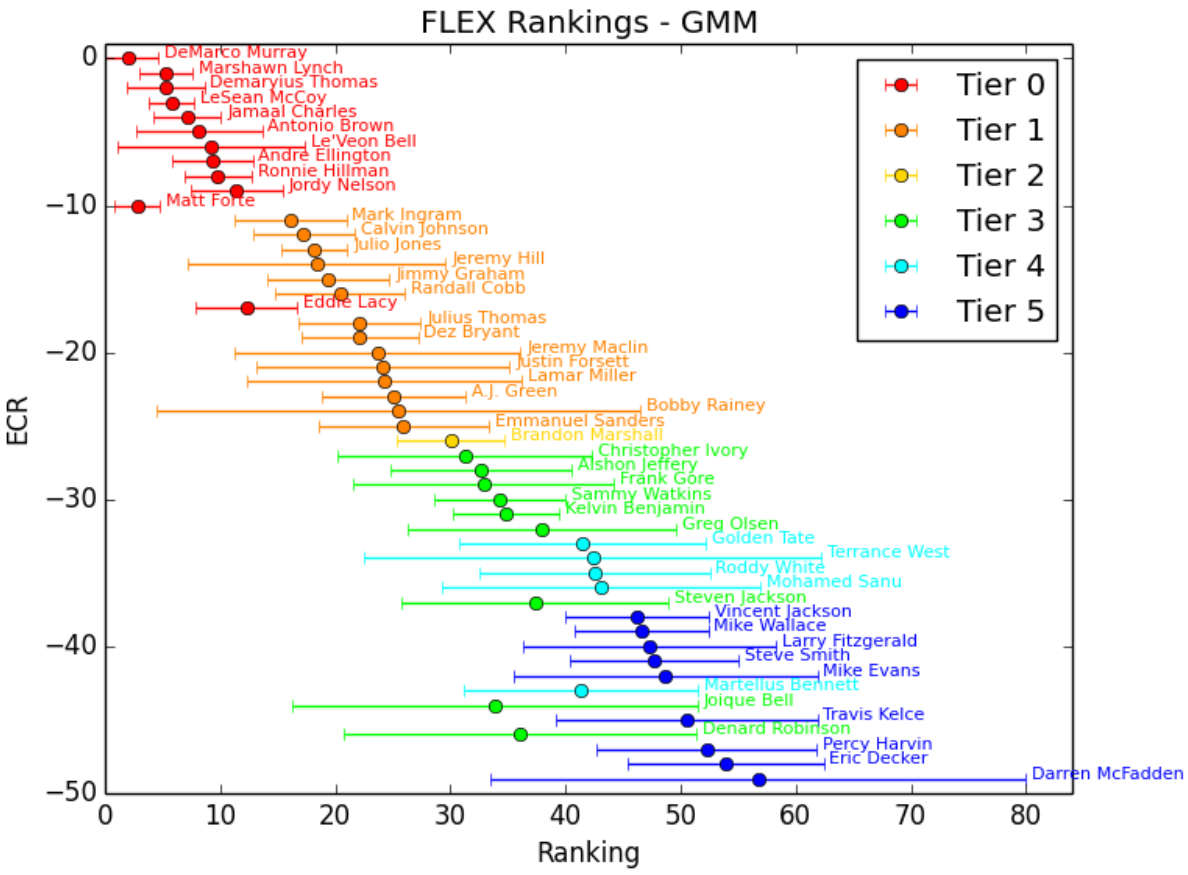

Figure 4: FLEX Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/te.png

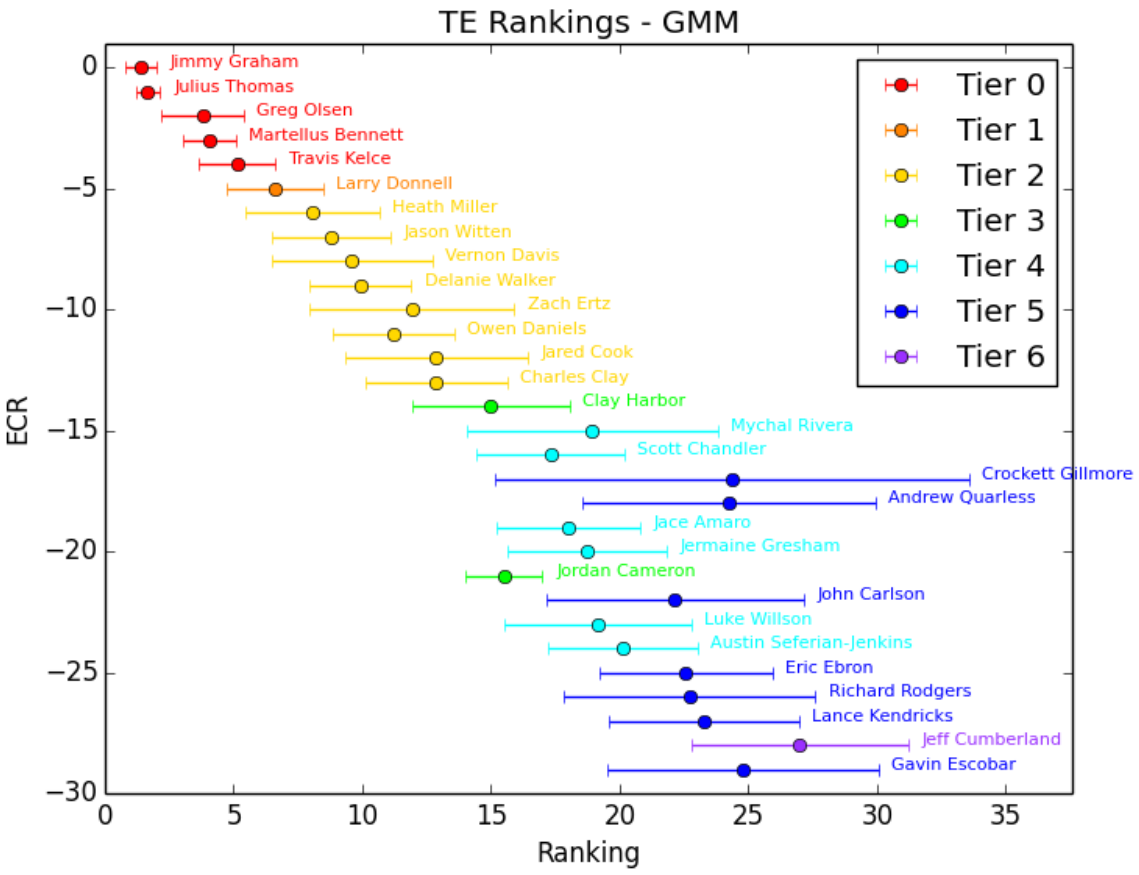

Figure 5: TE Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/k.png

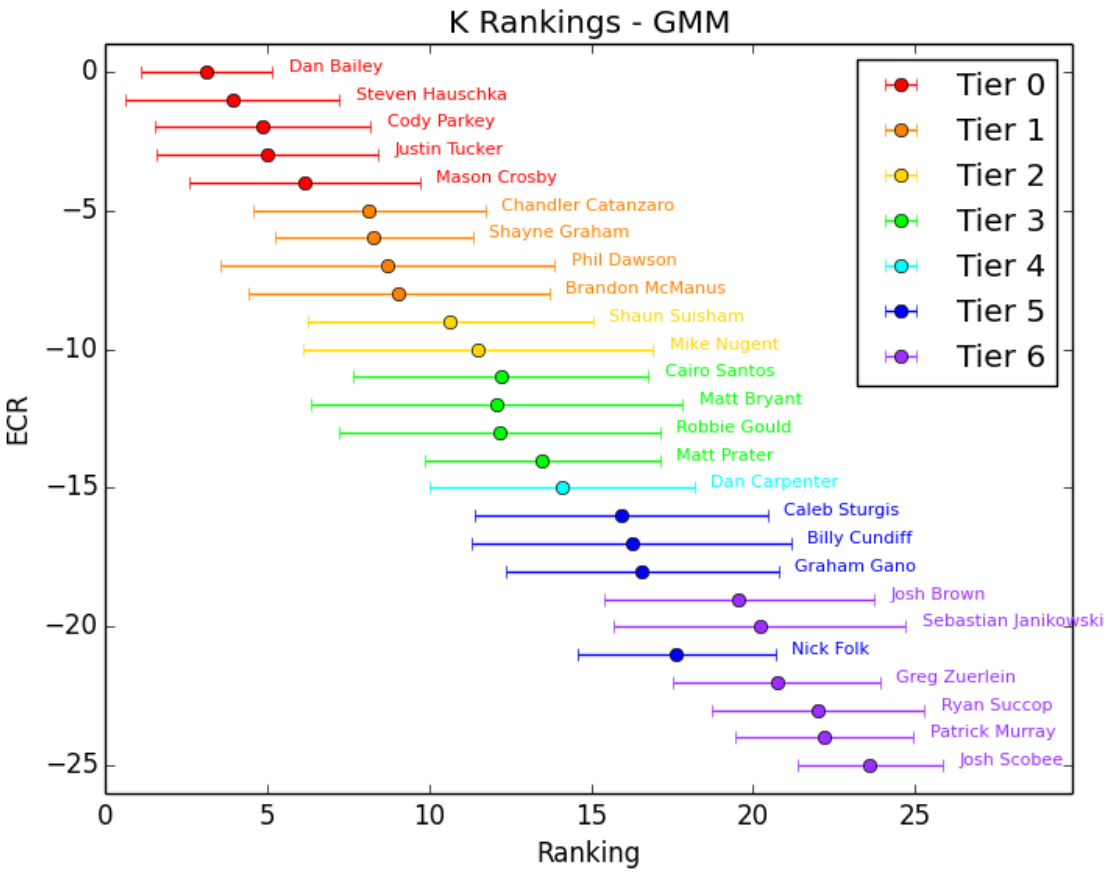

Figure 6: K Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ppr-rb.png

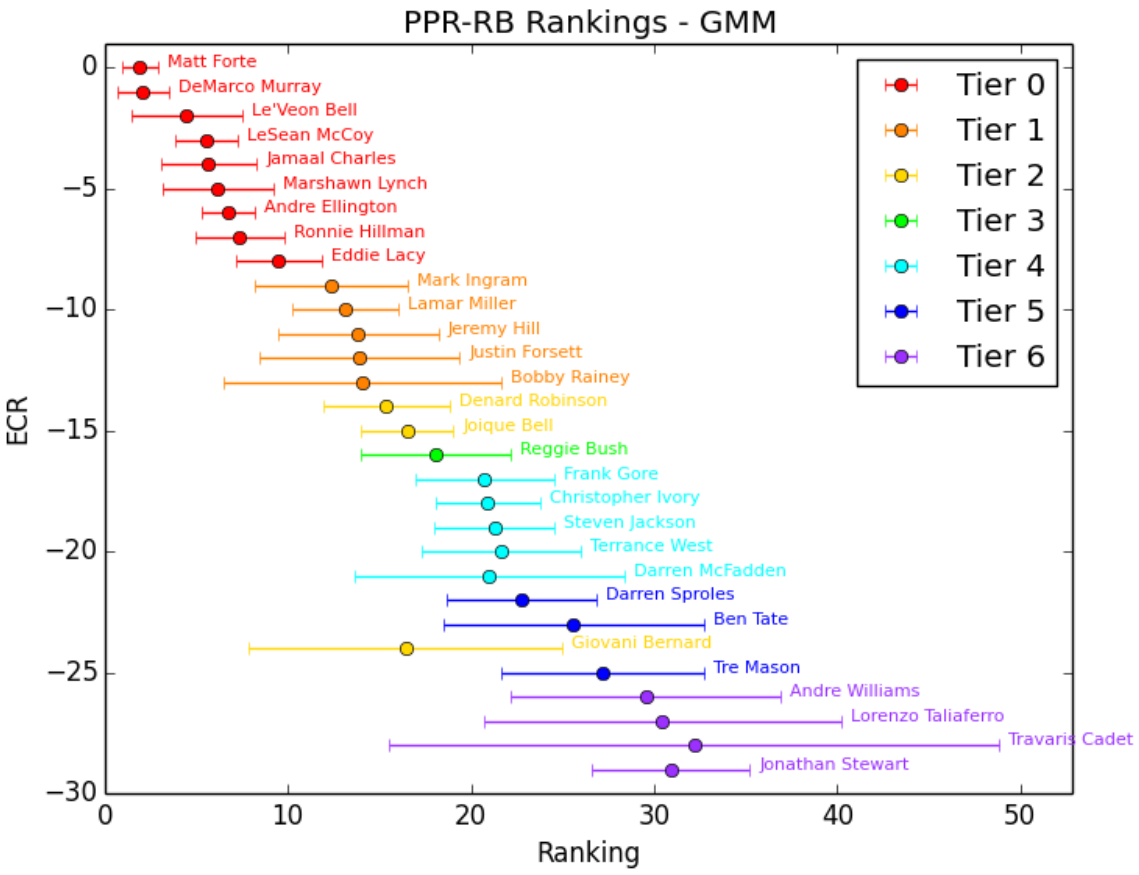

Figure 7: PPR-RB Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ppr-wr.png

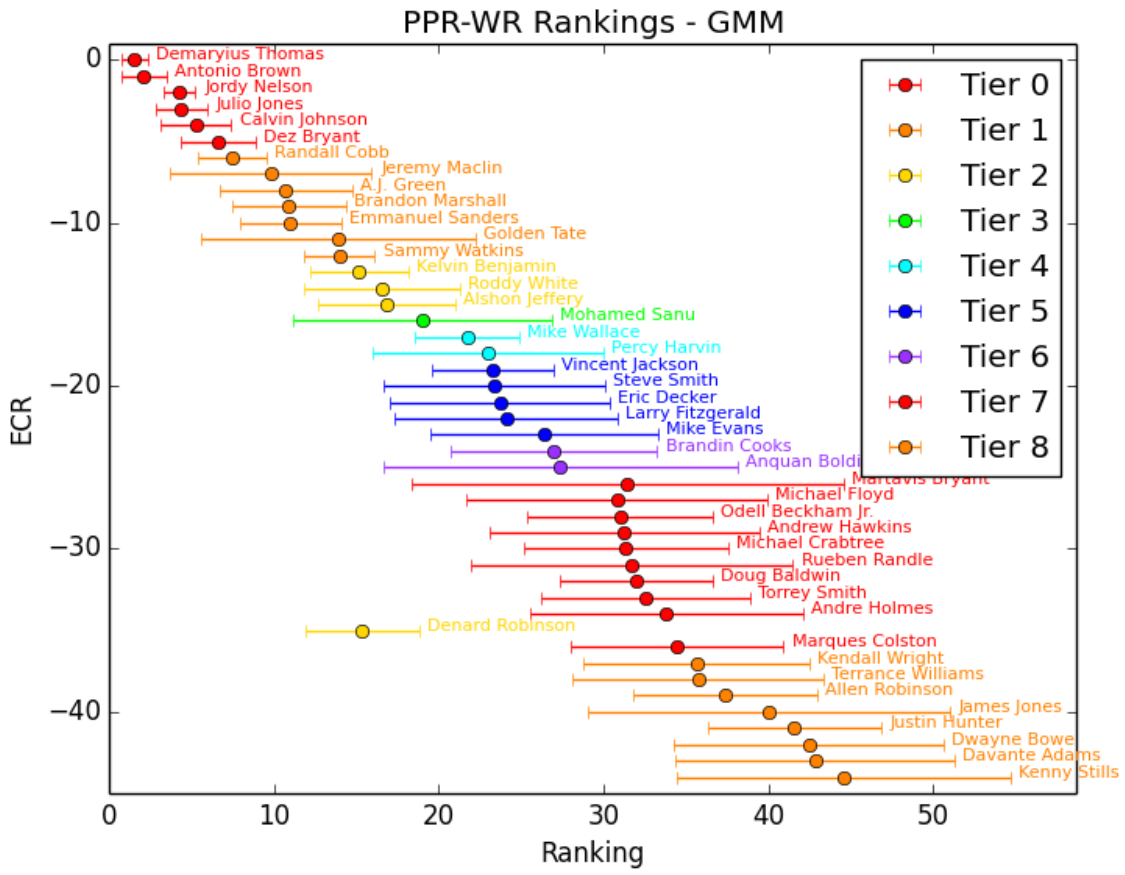

Figure 8: PPR-WR Tiered Rankings

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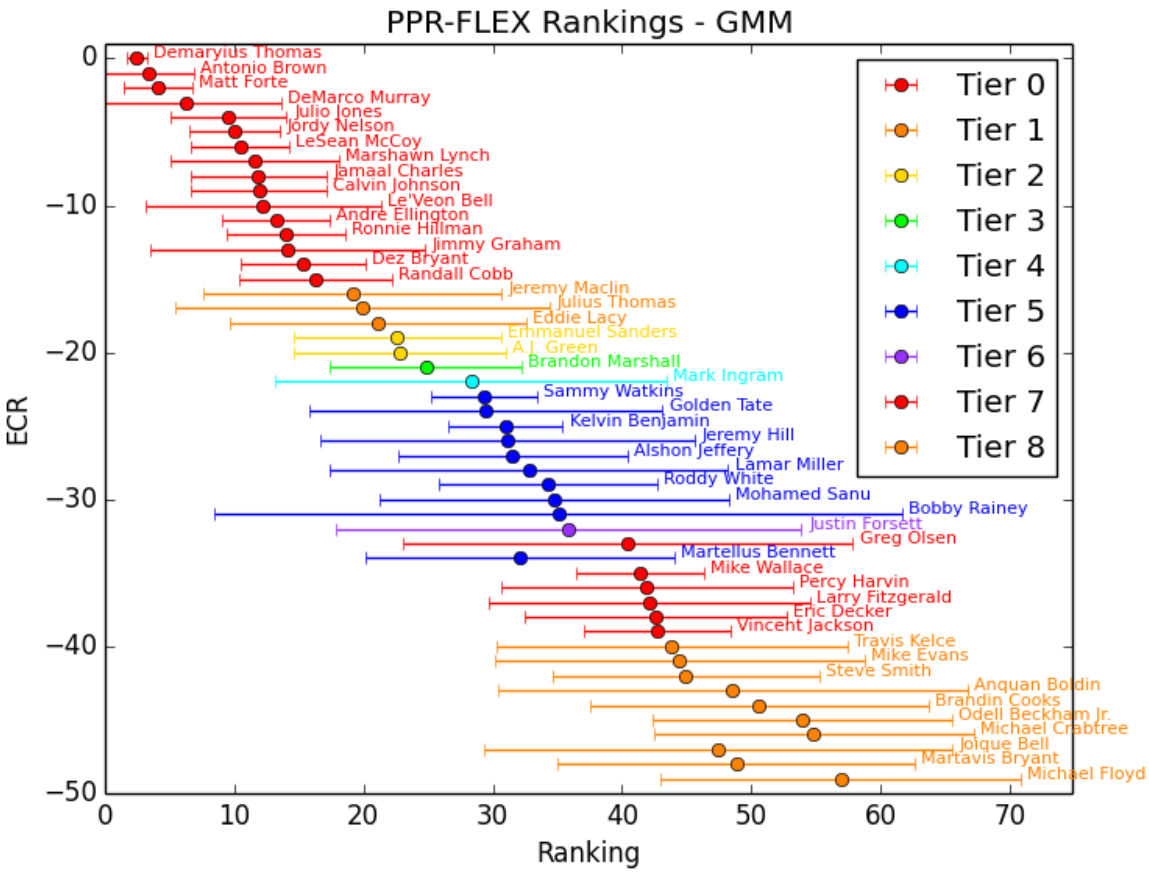

Figure 9: PPR-FLEX Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ppr-te.png

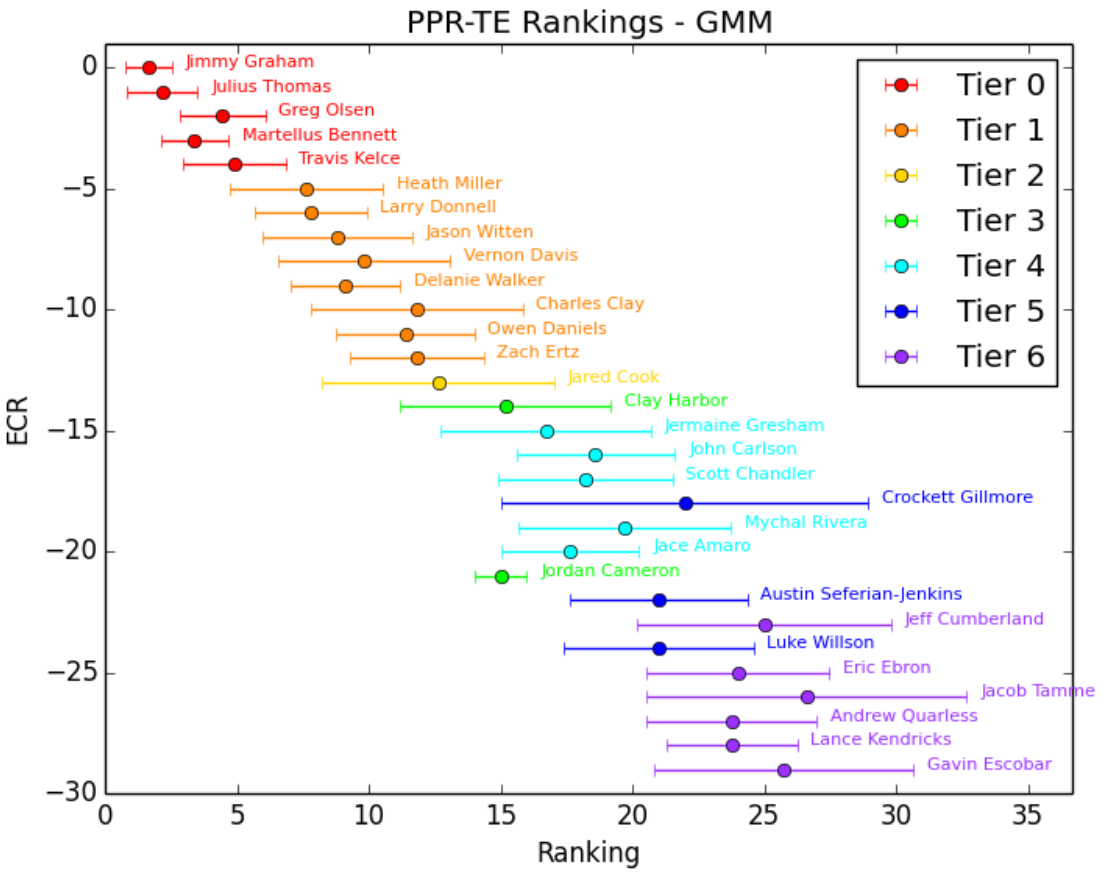

Figure 10: PPR-TE Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ros-qb.png

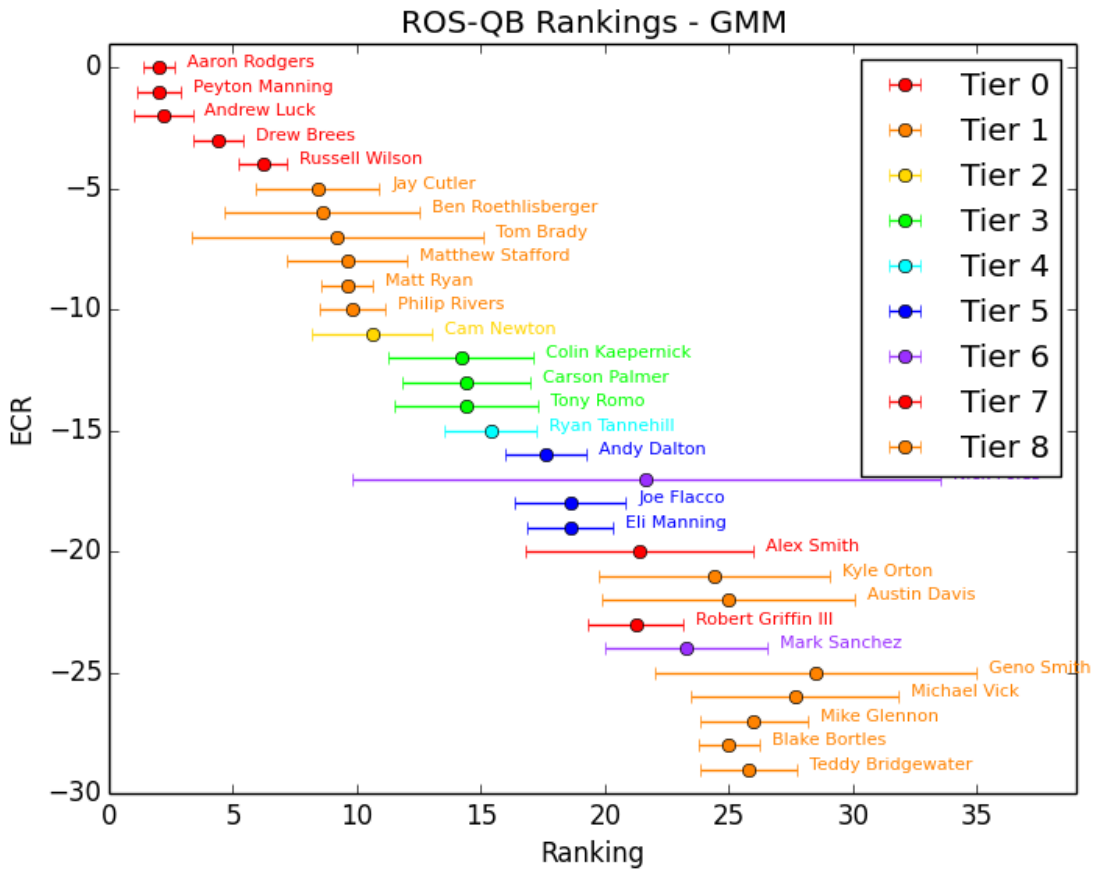

Figure 11: ROS-QB Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ros-rb.png

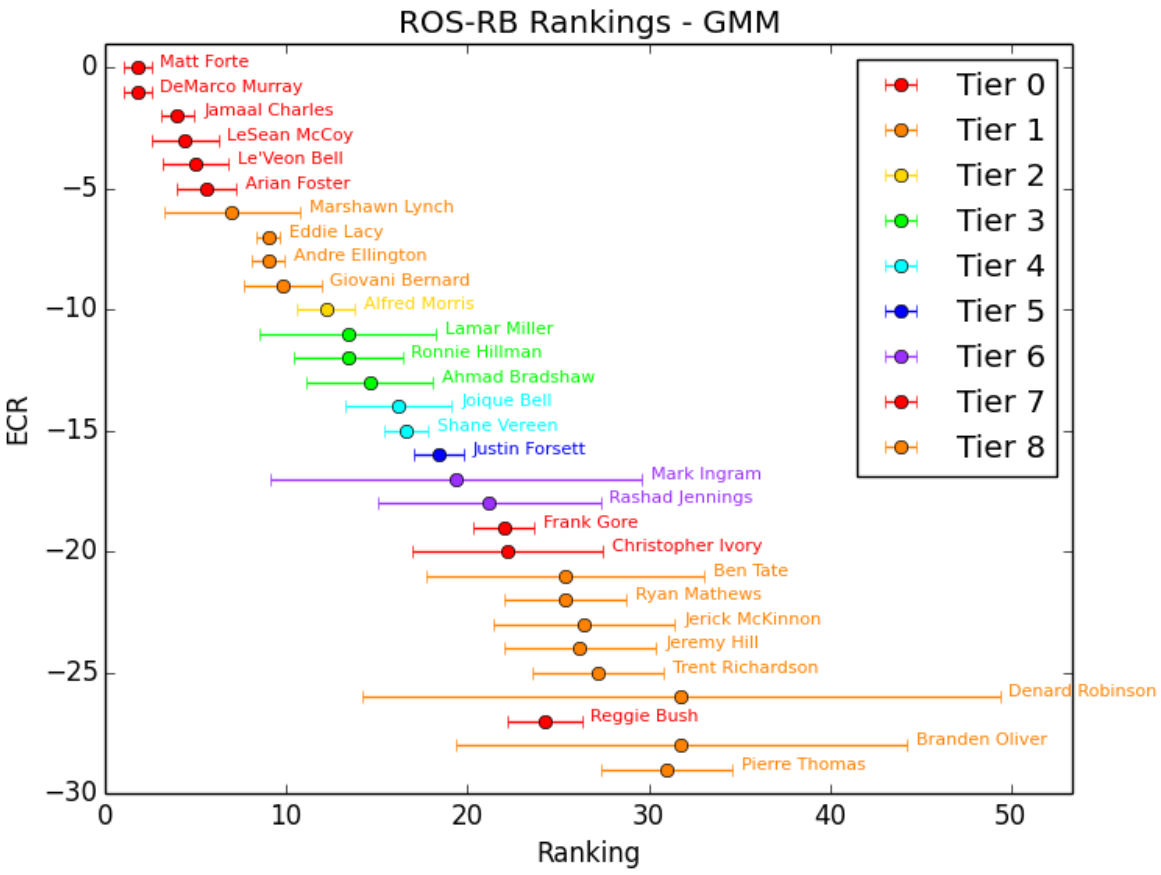

Figure 12: ROS-RB Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ros-wr.png

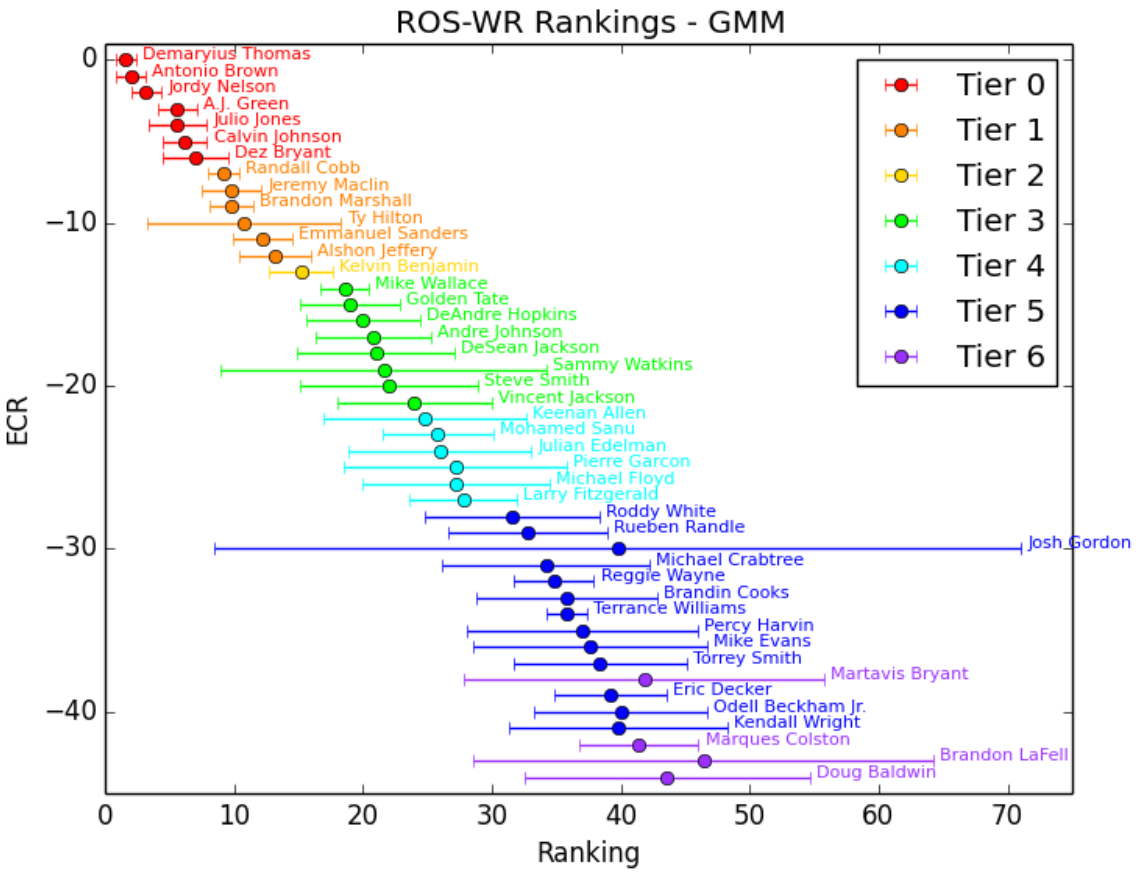

Figure 13: ROS-WR Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ros-flex.png

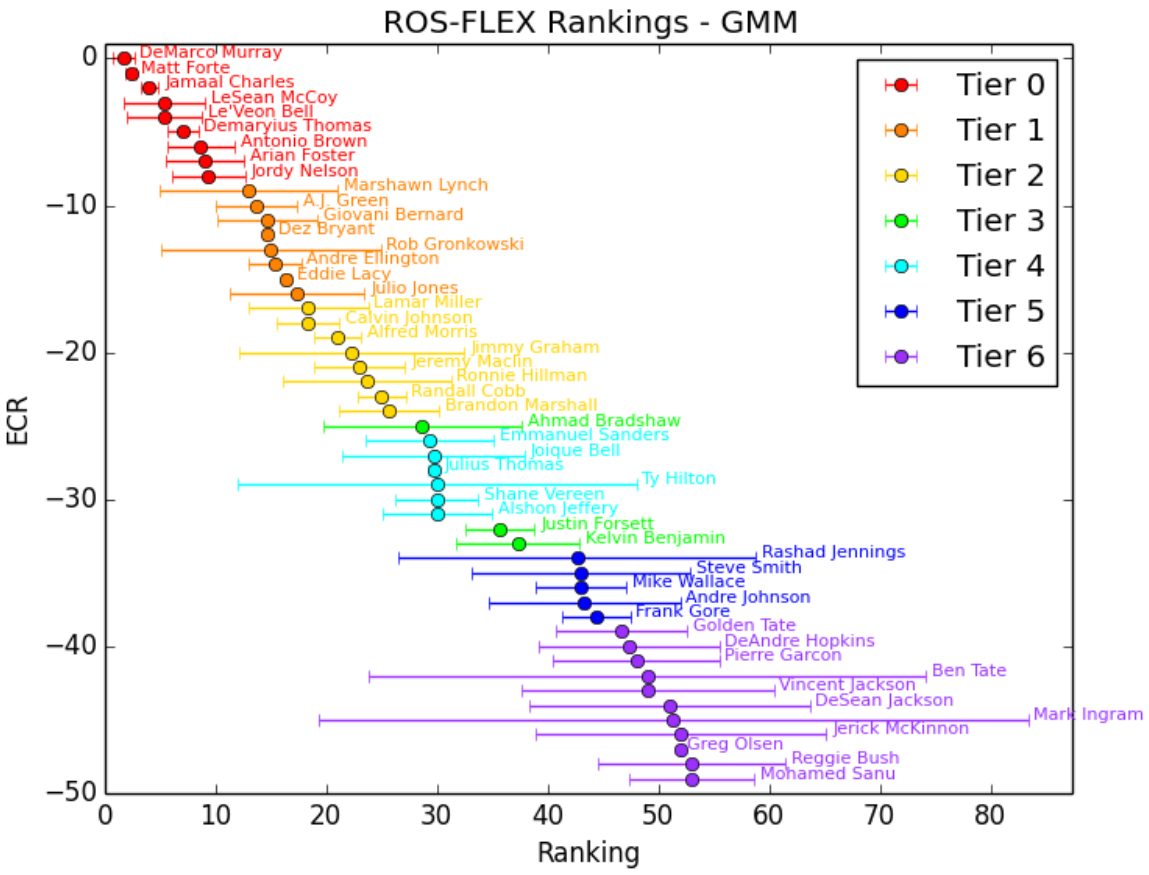

Figure 14: ROS-FLEX Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ros-te.png

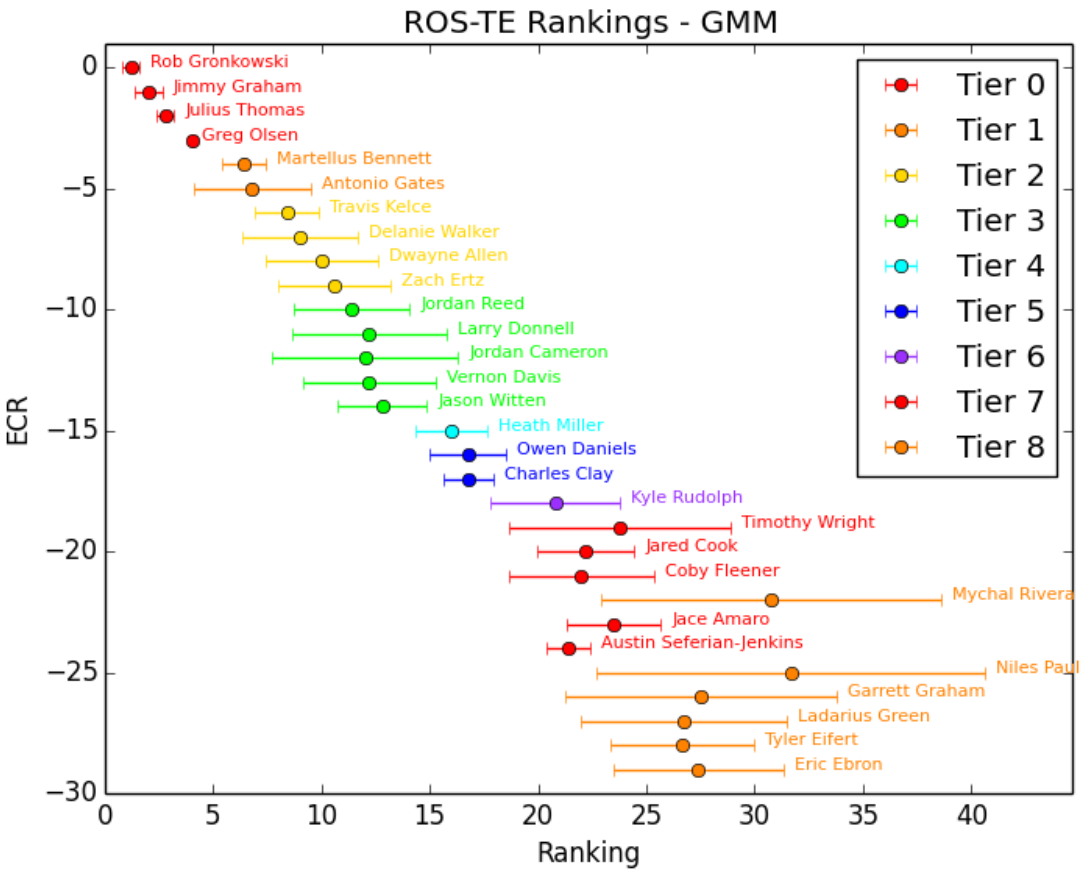

Figure 15: ROS-TE Tiered Rankings

Drive/Developer Projects/Python/pyffl/data/generated/tiered/ros-k.png

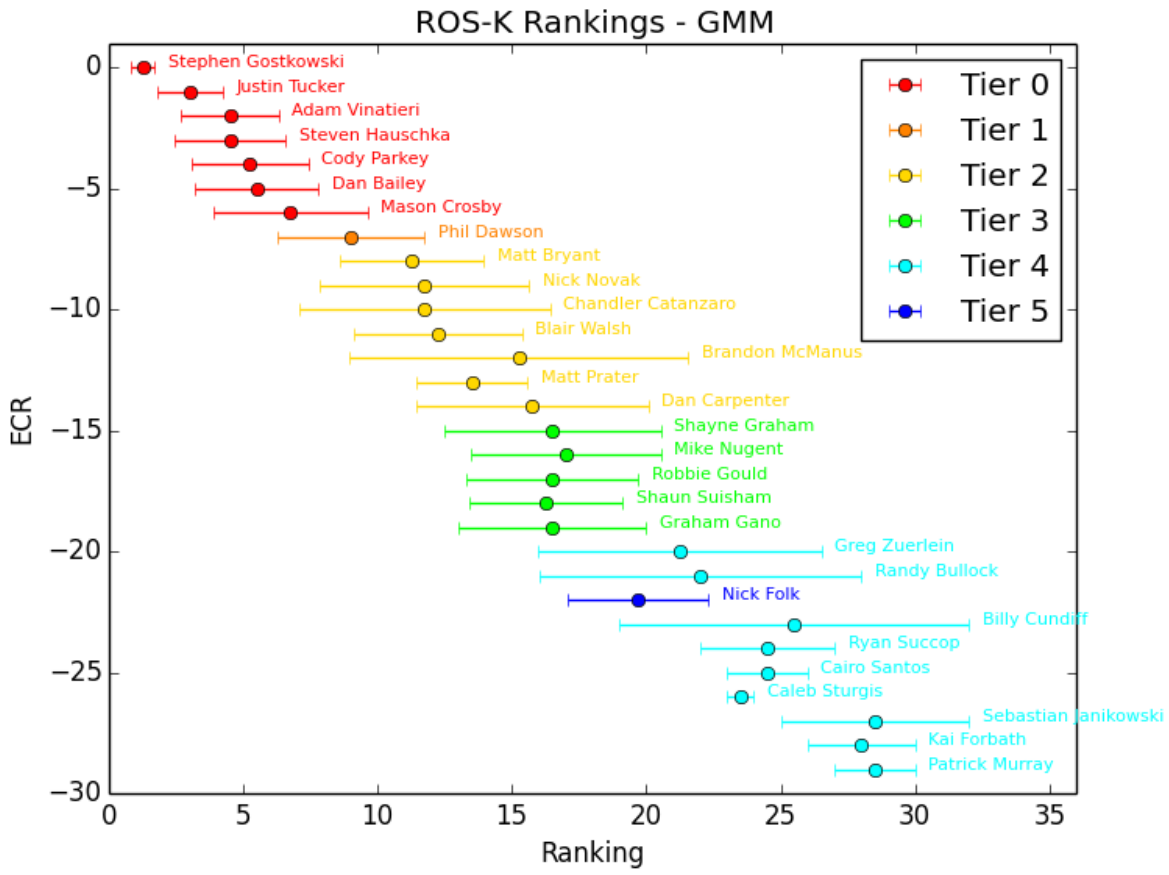

Figure 16: ROS-K Tiered Rankings

Rushing Statistics

Motivation

Understanding a team's rushing habits can help us get discover vital trends to picking RBs.
TODO: Finish Motivation

Teams sorted by % of their rushing offensive plays

Team	Percentage
1. HOU	51.0791%
2. DAL	50.9761%
3. CLE	49.3671%
4. KC	47.9381%
5. SEA	47.2222%
6. NYG	46.5066%
7. SF	45.5531%
8. BAL	44.7598%
9. CIN	44.4142%
10. SD	43.6759%
11. NYJ	43.5622%
12. GB	42.6829%
13. MIN	42.5676%
14. TEN	42.3267%
15. MIA	42.2886%
16. ARI	42.1053%
17. DEN	42.0000%
18. NE	41.9565%
19. PIT	41.2393%
20. IND	41.0781%
21. PHI	40.4878%
22. DET	40.1302%
23. STL	39.7436%
24. CAR	39.1685%
25. BUF	38.8889%
26. WAS	38.6364%
27. CHI	36.5688%
28. NO	35.7995%
29. TB	35.5301%
30. JAC	35.2535%
31. ATL	33.8530%
32. OAK	33.6364%

Receiving Statistics

Motivation

Understanding a team's receiving habits can help us get discover vital trends to picking WRs.

TODO: Finish Motivation

Teams sorted by % of their passing offensive plays

Team	Percentage
1. OAK	64.8485%
2. ATL	62.8062%
3. NO	62.7685%
4. TB	60.4585%
5. CHI	59.5937%
6. WAS	58.1818%
7. JAC	58.0645%
8. PHI	57.8049%
9. CAR	57.5492%
10. BUF	56.8889%
11. IND	56.8773%
12. DEN	56.2222%
13. STL	56.1538%
14. NE	55.0000%
15. ARI	55.0000%
16. DET	54.6638%
17. PIT	54.4872%
18. MIA	54.2289%
19. CIN	53.9510%
20. SD	53.7549%
21. BAL	53.4934%
22. TEN	53.2178%
23. GB	53.1707%
24. NYJ	52.5751%
25. MIN	51.3514%
26. SF	50.3254%
27. NYG	50.2183%
28. SEA	48.8889%
29. CLE	48.3544%
30. KC	47.9381%
31. DAL	46.4208%
32. HOU	46.2830%

Top 15 people who catch a pass on any given pass by their team (%)

Player	Percentage
1. Jordy Nelson	21.5596%
2. Dez Bryant	21.0280%
3. Andre Johnson	20.2073%
4. Matt Forte	19.6970%
5. Antonio Brown	19.6078%
6. Golden Tate	19.0476%
7. Demaryius Thomas	18.5771%
8. Emmanuel Sanders	18.5771%
9. Julian Edelman	17.3913%
10. Julio Jones	17.3759%
11. Anquan Boldin	16.8103%
12. DeAndre Hopkins	16.0622%
13. Randall Cobb	16.0550%
14. Keenan Allen	15.8088%
15. Greg Olsen	15.5894%

Top 15 people who will catch a pass on any given offensive play by their team (%)

Player	Percentage
1. Matt Forte	11.7381%
2. Jordy Nelson	11.4634%
3. Julio Jones	10.9131%
4. Antonio Brown	10.6838%
5. Demaryius Thomas	10.4444%
6. Emmanuel Sanders	10.4444%
7. Golden Tate	10.4121%
8. Dez Bryant	9.7614%
9. Julian Edelman	9.5652%
10. Andre Johnson	9.3525%
11. Martellus Bennett	9.2551%
12. James Jones	9.0909%
13. Greg Olsen	8.9716%
14. T.Y. Hilton	8.7361%
15. Randall Cobb	8.5366%

Top 15 people who will score a receiving touchdown on any given pass by their team (%)

Player	Percentage
1. Randall Cobb	3.6697%
2. Julius Thomas	3.5573%
3. Antonio Gates	3.3088%
4. Terrance Williams	2.8037%
5. Jordy Nelson	2.7523%
6. Demaryius Thomas	2.3715%
7. Mike Wallace	2.2936%
8. Ahmad Bradshaw	1.9608%
9. Antonio Brown	1.9608%
10. Greg Olsen	1.9011%
11. Kelvin Benjamin	1.9011%
12. Brandon Marshall	1.8939%
13. Dez Bryant	1.8692%
14. Kendall Wright	1.8605%
15. Eddie Royal	1.8382%

Top 15 people who will score a receiving touchdown on any given offensive play by their team (%)

Player	Percentage
1. Julius Thomas	2.0000%
2. Randall Cobb	1.9512%
3. Antonio Gates	1.7787%
4. Jordy Nelson	1.4634%
5. Demaryius Thomas	1.3333%
6. Terrance Williams	1.3015%
7. Mike Wallace	1.2438%
8. Brandon Marshall	1.1287%
9. Ahmad Bradshaw	1.1152%
10. Greg Olsen	1.0941%
11. Kelvin Benjamin	1.0941%
12. Antonio Brown	1.0684%
13. Kendall Wright	0.9901%
14. Eddie Royal	0.9881%
15. Jeremy Maclin	0.9756%

RB Visualizations

Motivation

Visualization of data is obviously very important. But often, as in the case of fantasy football, it can be crucial to making sense of data that normally very difficult to interpret. This post was inspired by the Fantasy Football Tier Visualiations performed by Boris Chen at the New York Times.

Note: Sorry if some of these are hard to read. I did my best to make them visible.

Name	Fantasy Points (Rushing)	Fantasy Points (Receiving)	Fumbles	Fantasy Points (Total)
DeMarco Murray	155.3	25.0	5	170.3
Marshawn Lynch	84.9	40.3	0	125.2
LeSean McCoy	68.2	9.4	2	73.6
Matt Forte	74.2	67.0	1	139.2
Jamaal Charles	73.5	22.9	2	92.4
Le'Veon Bell	77.1	55.3	0	132.4
Andre Ellington	67.9	43.3	2	107.2
Ronnie Hillman	54.5	18.8	1	71.3
Eddie Lacy	66.8	20.9	2	83.7
Mark Ingram	79.1	4.8	0	83.9
Jeremy Hill	64.9	14.0	0	78.9
Denard Robinson	54.3	5.7	0	60.0
Justin Forsett	78.9	20.2	1	97.1
Bobby Rainey	43.4	27.4	3	64.8
Lamar Miller	81.8	20.4	3	96.2
Christopher Ivory	79.7	10.3	0	90.0
Frank Gore	53.2	13.7	0	66.9
Terrance West	42.2	9.9	0	52.1
Joique Bell	49.3	13.7	2	59.0
Steven Jackson	52.5	6.0	0	58.5
Darren McFadden	47.8	16.1	1	61.9
Ben Tate	48.8	3.3	0	52.1
Reggie Bush	23.1	16.4	0	39.5
Lorenzo Taliaferro	48.7	9.4	1	56.1
Tre Mason	28.2	0.5	1	26.7
Andre Williams	40.0	2.5	0	42.5
Darren Sproles	40.8	24.4	1	63.2
Jonathan Stewart	32.3	8.5	0	40.8
Giovani Bernard	74.6	17.9	0	92.5
DeAngelo Williams	12.6	3.0	0	15.6

Drive/Developer Projects/Python/pyffl/data/generated/rb/1.png

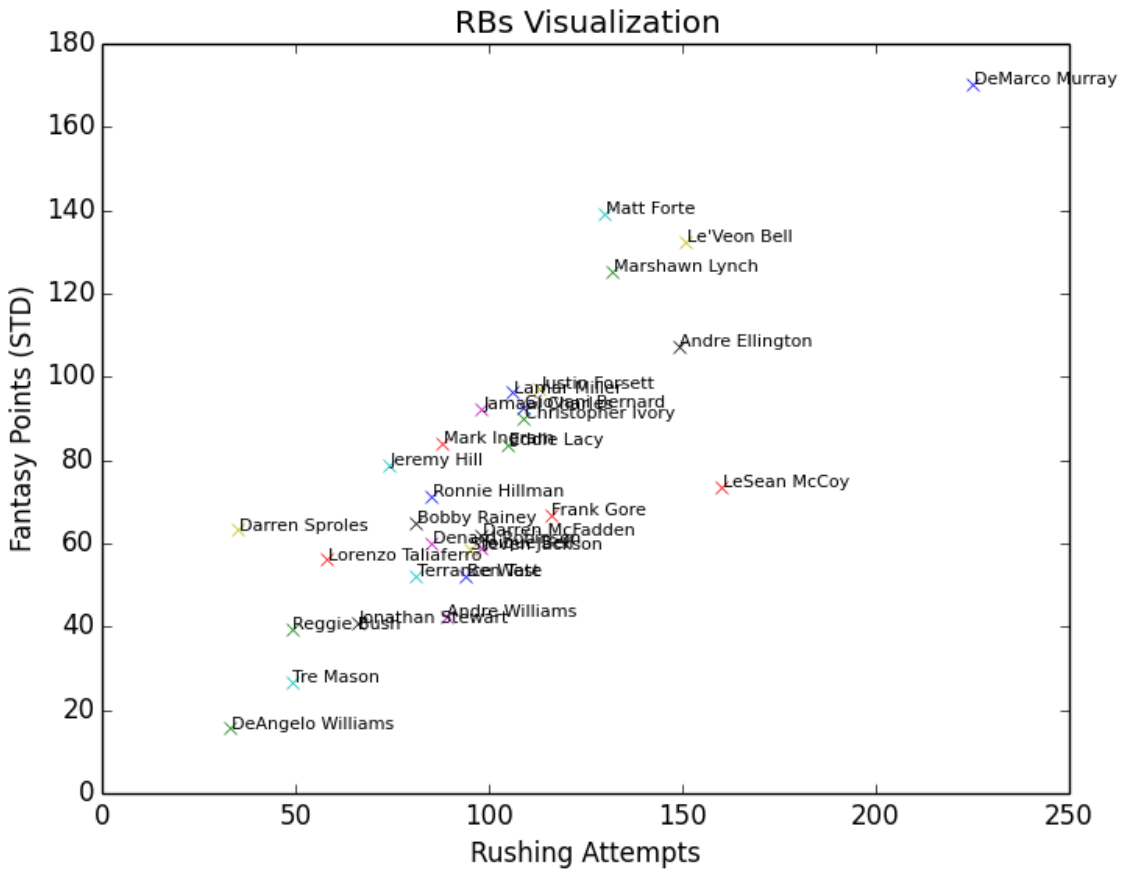

Figure 17: RB Visualization 1

Drive/Developer Projects/Python/pyffl/data/generated/rb/2.png

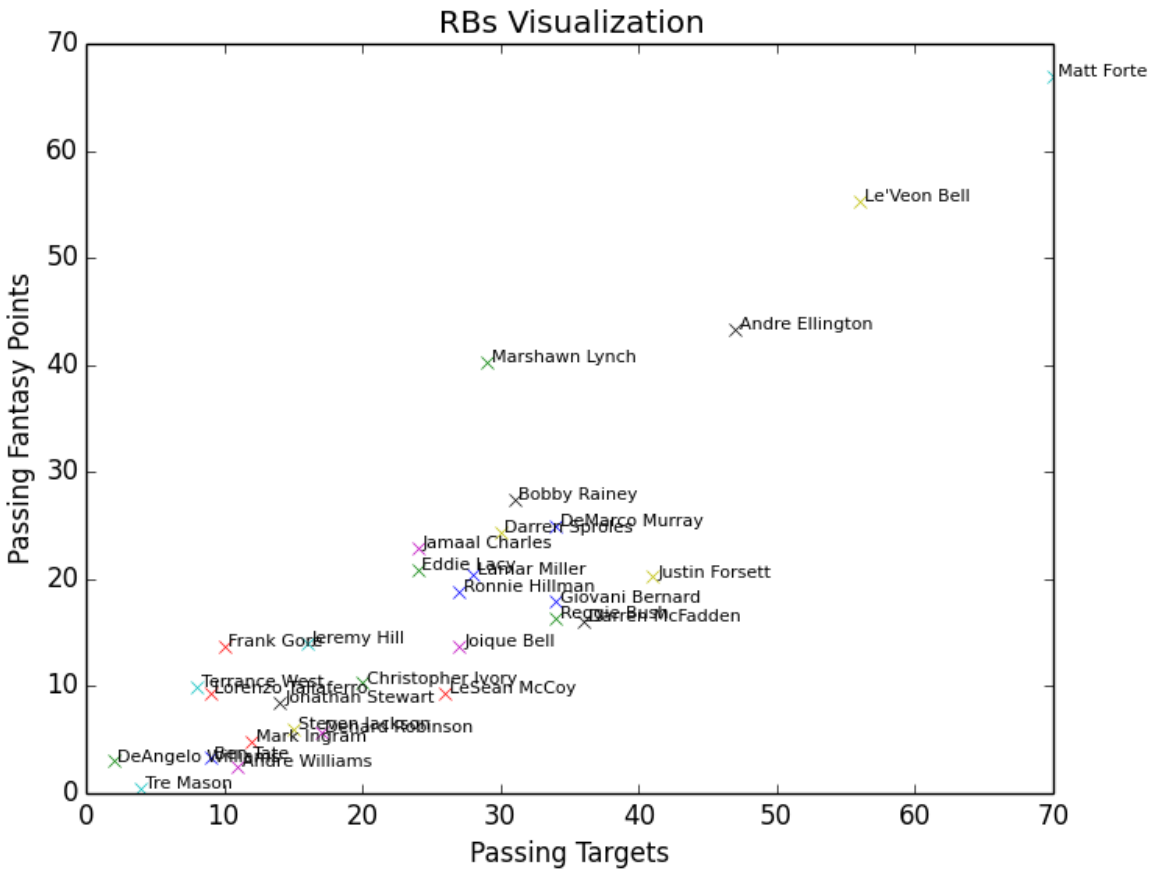

Figure 18: RB Visualization 2

Drive/Developer Projects/Python/pyffl/data/generated/rb/3.png

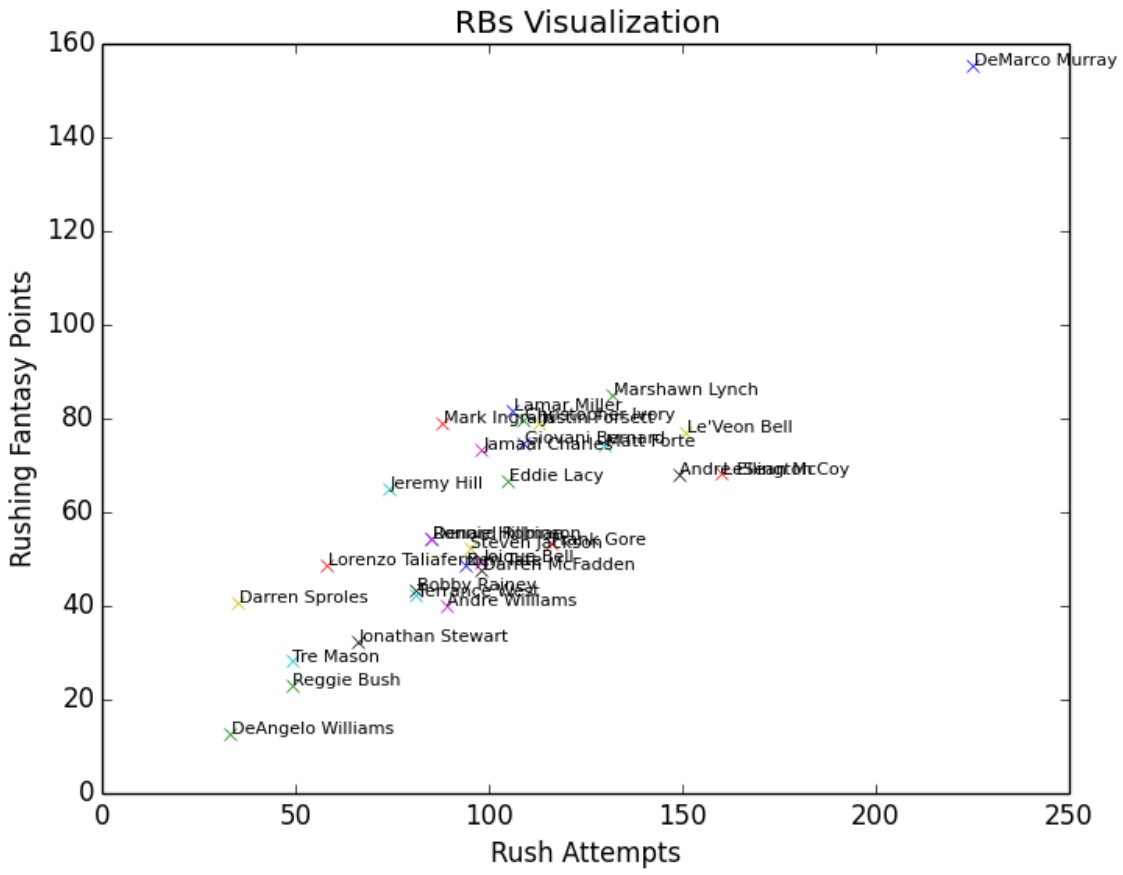

Figure 19: RB Visualization 3

Drive/Developer Projects/Python/pyffl/data/generated/rb/4.png

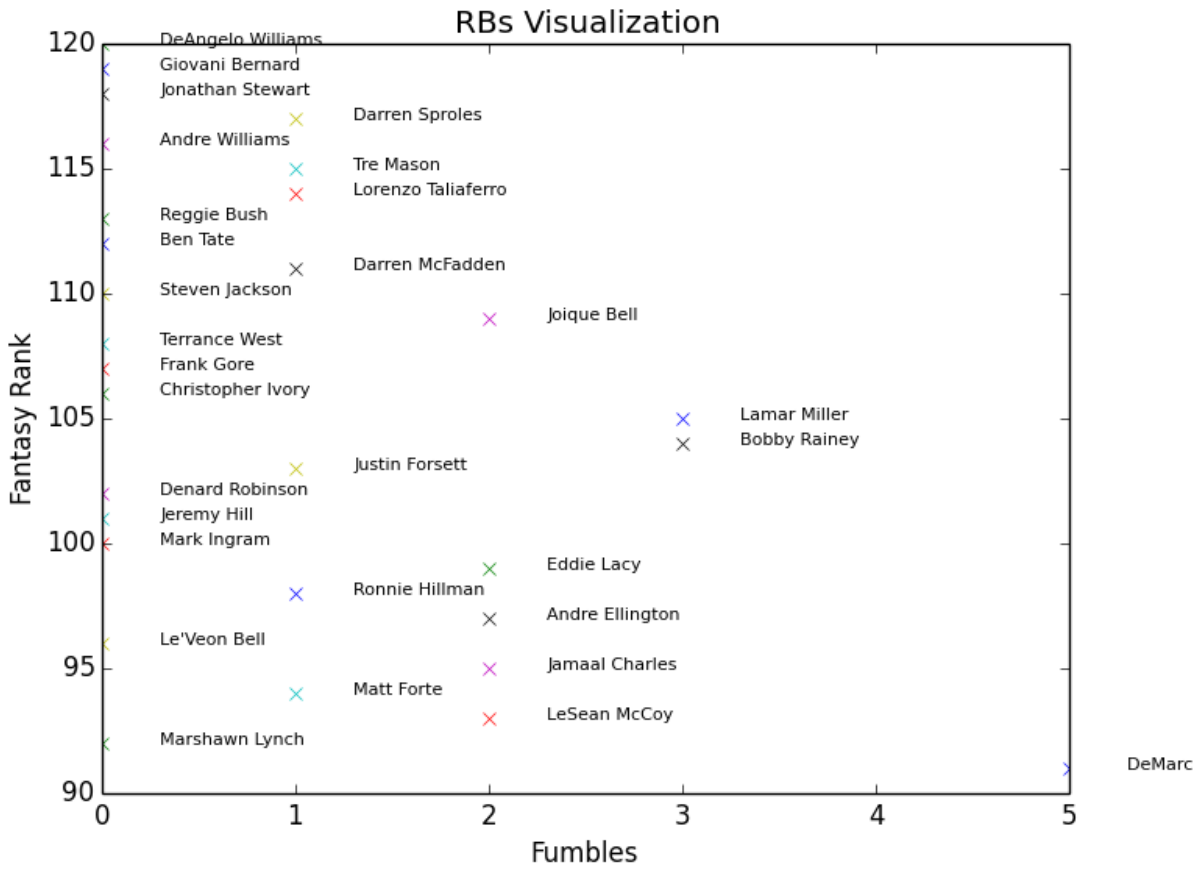

Figure 20: RB Visualization 4

WR Visualizations

Motivation

Visualization of data is obviously very important. But often, as in the case of fantasy football, it can be crucial to making sense of data that normally very difficult to interpret. This post was inspired by the Fantasy Football Tier Visualiations performed by Boris Chen at the New York Times.

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Drive/Developer Projects/Python/pyffl/data/generated/wr/1.png

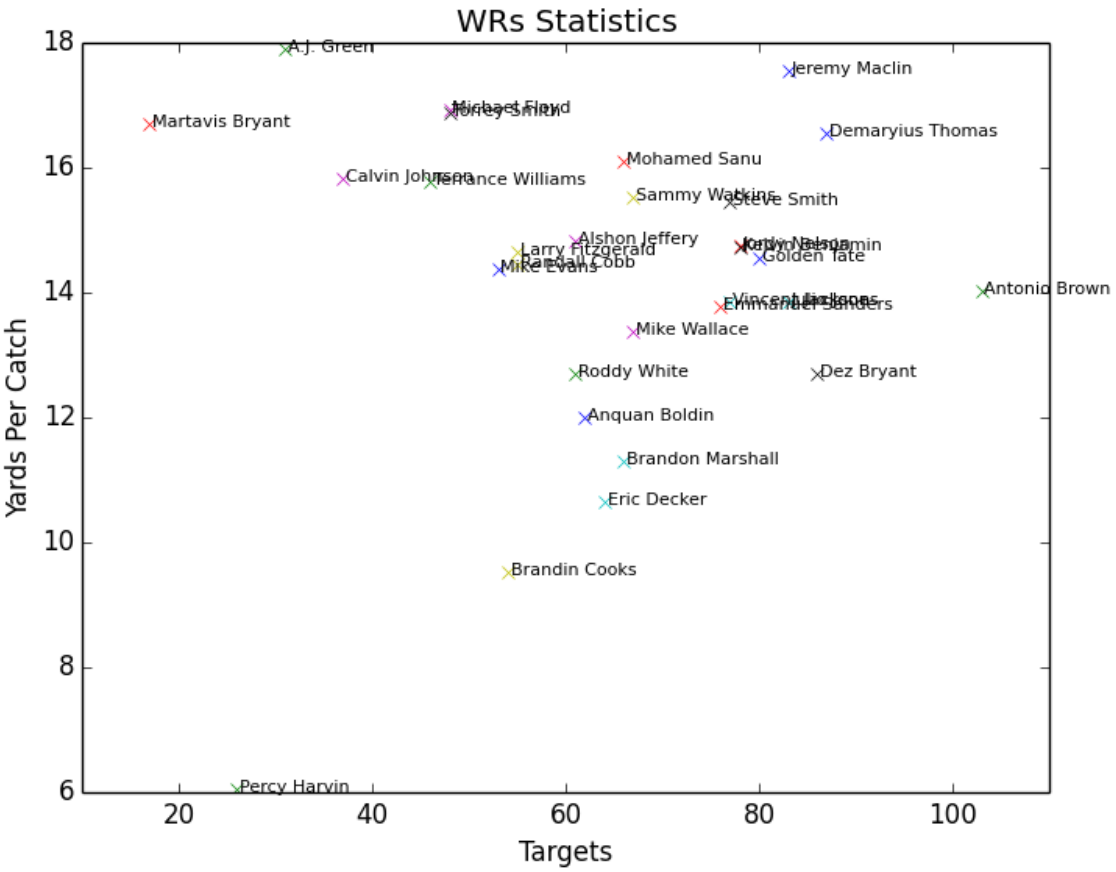

Figure 21: WR Visualization 1

Drive/Developer Projects/Python/pyffl/data/generated/wr/2.png

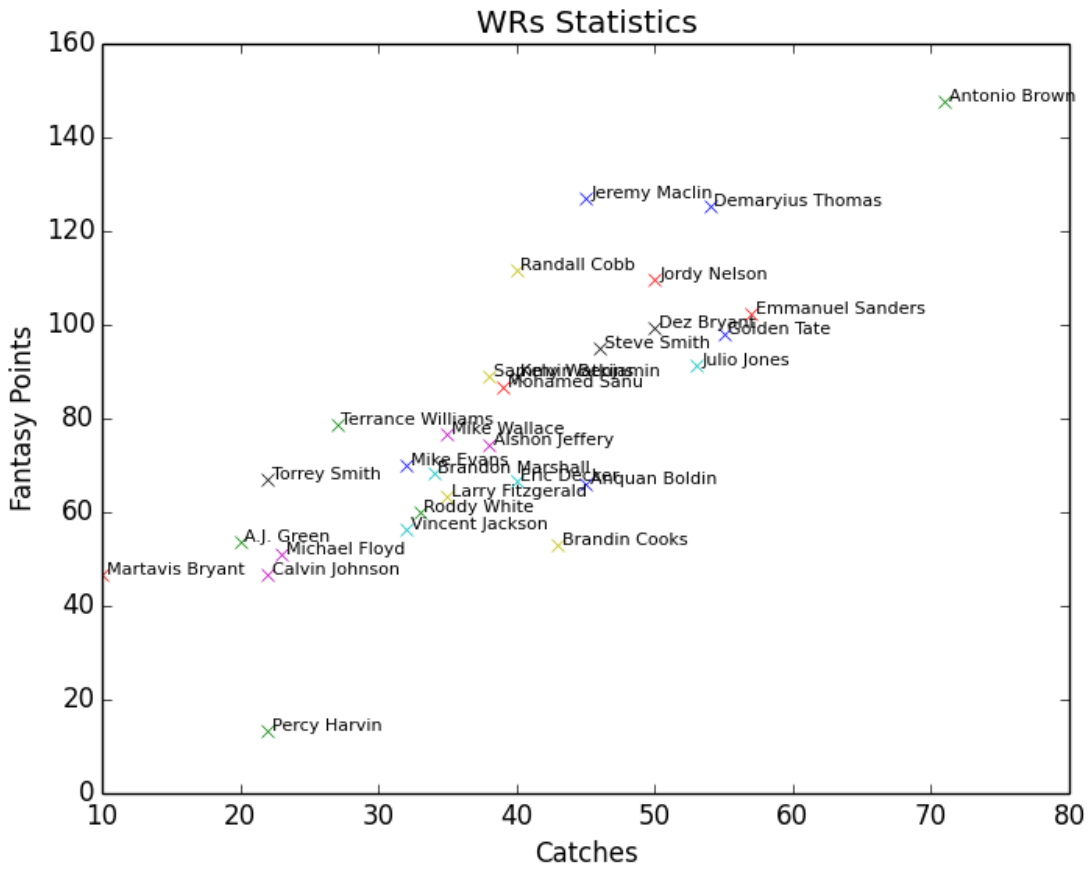

Figure 22: WR Visualization 2

Drive/Developer Projects/Python/pyffl/data/generated/wr/3.png

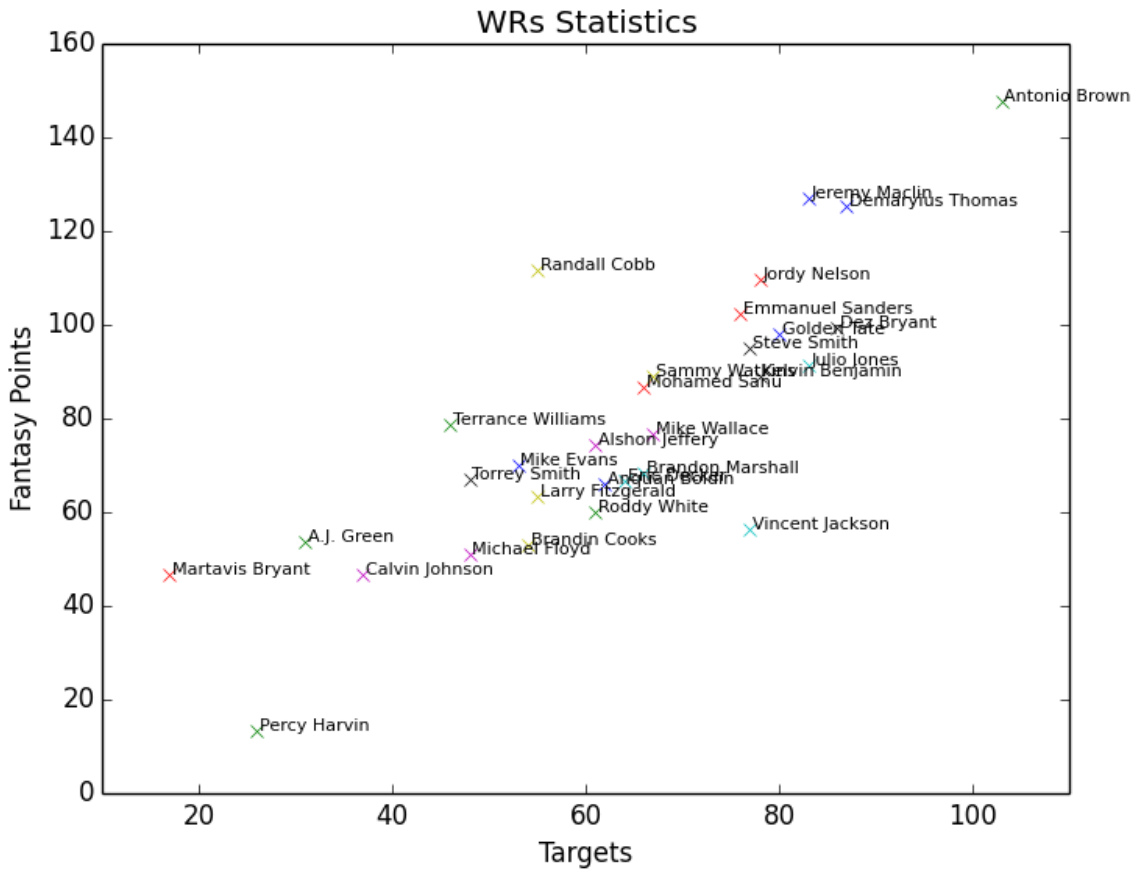

Figure 23: WR Visualization 3

Drive/Developer Projects/Python/pyffl/data/generated/wr/4.png

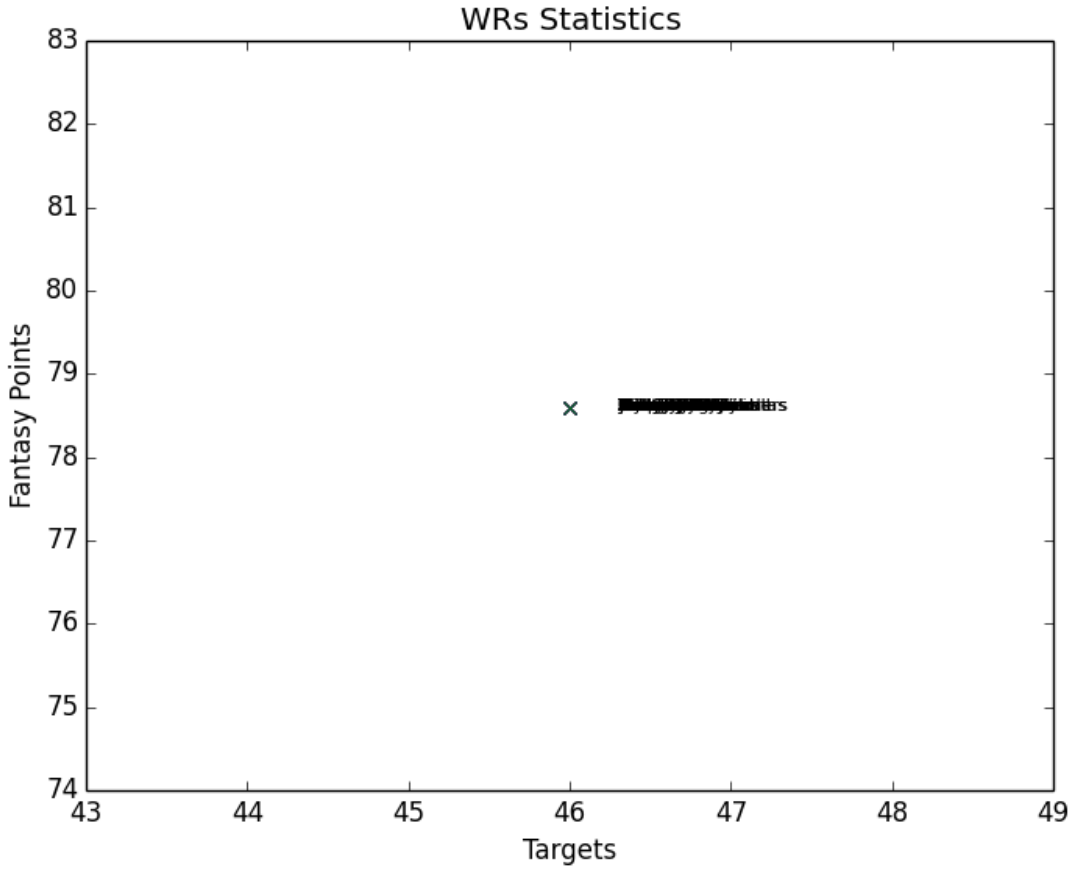

Figure 24: WR Visualization 4

DPS Graphs

DPS Analysis Overview

- DPS (Delta Ranking per STD) is a metric I'm fine tuning to perform all sorts of automated player analysis, such as buy-sell-hold labeling and sleeper detection. This model treats player's like stock and the trades / waiver wire pickups as the stock market. Just like the real stock market, projecting how a player's performance to date vs. how experts say that stock should perform in the future can be really helpful in a number of ways.
- The first rule is to understand that this chart is a tool, not a guideline. Just like an expert's stock market analysis, it can only suggest players who are undervalued or overvalued for you to go out and research. This chart is not predicting a player's performance in the future. In fact, it's not predicting anything at all - It simply looking at how the player has done compared to the overall consensus on how he should be doing.
- Please remember that this chart has absolutely no idea what the public's general consensus about that player is. Since that is something that is outside the realm of this algorithm, it simply suggests players that might be good to pickup and leaves the rest of the analysis to you! Here is a post I made to address this idea in a statistical sense:
- I essentially separate two measures of performance - how experts say a player should be playing and how they are actually playing. Note that there is no mention of how the general public feels about each player, as that is extremely hard to quantify reliably. So the phenomena that you are talking about (and most of the confusion about this metric) stems from the idea that whether a player is "underperforming" and whether a player is "tradeable" are not equivalent. If you want to talk about this statistically, basically this means that figuring out if a player is tradeable is not a pure function of their past performance - there is some other factor in the equation that takes into account how popular a player is, when he was drafted, intangibles, etc. This is why I say in the description that this is a tool, not a guideline - since it's too difficult to quantify, this graph solves half of the "buy low, sell high" equation and leaves the incalculable part to your discretion.

The Metrics

- DPS is the Delta per Std metric. This is the equivalent of looking at a player's current fantasy ranking (regardless of whether they have been on a bye/injured or not) and comparing it to where the general consensus on that player is. The formula goes like this ((where players are actually ranked) - (where experts, on average, say they should be ranked)) / (that player's standard deviation). Use this to determine who is a high sell/low buy when dealing with an inexperienced FFL player.
- DPS Adjusted is the same thing as DPS, but this metric does account for whether a player has missed a game from injury or a bye. This metric is probably better to use if your league is packed with experienced FFL players like mine.
- Sleeper/Dump is an algorithmic approximation for whether a player could be a potential sleeper or dump. This algorithm simply checks whether a projected player is outside the top 2/3 of the pack in their respective position and has a good potential to greatly improve. If a player has been out on injury, sometimes they will show up as a Sleeper. There is not any reliable way to account for this in the simulation, so we will all just have to be okay with that and use our heads. This does not mean that every player labelled sleeper is actually a sleeper! The algorithm has no idea what the general public's perception of a certain player is, because that is not readily quantifiable. Therefore, it can't take into account that your player was drafted very high and has been underperforming.

How To Use This Chart

- Again, remember that this chart is a tool, not a guideline. It can only suggest players who are undervalued or overvalued for you to go out and research. This chart is not predicting a player's

performance in the future. In fact, it's not predicting anything at all - It simply looking at how the player has done compared to the overall consensus on how he should be doing.

- Roughly speaking, positive numbers mean a player will increase in ranking (possible buy) and negative numbers mean that player will decline in ranking (possible sell). Anywhere near 0 means they will keep about the same rank (possibly hold). Obviously, the greater the magnitude, the higher degree of that statistic..

DPS Rankings - QB

Rank	Player	DPS	DPS Adjusted	(S)leeper/(D)ump
1	Peyton Manning	2.41	0.3	
2	Ben Roethlisberger	-0.58	-0.06	
3	Aaron Rodgers	3.46	0.43	
4	Russell Wilson	-1.97	-0.25	
5	Drew Brees	3.67	0.46	
6	Jay Cutler	0.46	0.06	
7	Joe Flacco	-2.05	-0.23	
8	Ryan Tannehill	-1.84	-0.23	
9	Matt Ryan	2.22	0.28	
10	Eli Manning	-2.95	-0.37	
11	Colin Kaepernick	0.41	0.05	
12	Matthew Stafford	2.2	0.27	
13	Tony Romo	0.68	0.09	
14	Cam Newton	2.38	0.3	
15	Andy Dalton	0.36	0.05	
16	Alex Smith	0.0	0.0	
17	Brian Hoyer	-2.51	-0.31	
18	Derek Carr	-2.61	-0.33	
19	Austin Davis	-1.04	-0.13	
20	Carson Palmer	3.99	0.8	
21	Mike Glennon	0.32	0.05	
22	Blake Bortles	0.3	0.04	
23	Geno Smith	-0.55	-0.07	
24	Kyle Orton	1.96	0.49	
25	Josh McCown	-1.05	-0.35	
26	Michael Vick	2.28	0.33	
27	Zach Mettenberger	0.69	0.34	
28	Brandon Weeden	0.64	0.21	
29	Mark Sanchez	4.69	4.69	Sleeper

DPS Rankings - RB

Rank	Player	DPS	DPS Adjusted	(S)leeper/(D)ump
1	DeMarco Murray	1.0	0.11	
2	Matt Forte	-0.92	-0.11	
3	Le'Veon Bell	-0.77	-0.09	
4	Marshawn Lynch	1.54	0.19	
5	Andre Ellington	-0.51	-0.06	
6	Justin Forsett	-1.65	-0.18	
7	Jamaal Charles	1.5	0.21	
8	Lamar Miller	-1.79	-0.22	
9	Giovani Bernard	-2.3	-0.33	
10	Christopher Ivory	-1.56	-0.17	
11	Eddie Lacy	1.59	0.2	
12	Mark Ingram	1.33	0.27	
13	Jeremy Hill	0.64	0.08	
14	LeSean McCoy	6.81	0.85	
15	Ronnie Hillman	3.73	0.62	
16	Frank Gore	0.0	0.0	
17	Bobby Rainey	0.73	0.09	
18	Antone Smith	-5.46	-0.68	
19	Darren Sproles	-1.32	-0.19	
20	Darren McFadden	0.0	0.0	
21	Joique Bell	0.92	0.13	
22	Rashad Jennings	-1.56	-0.31	
23	Denard Robinson	6.33	0.7	
24	Steven Jackson	1.32	0.17	
25	Lorenzo Taliaferro	0.28	0.03	
26	Chris Johnson	-1.66	-0.18	
27	Andre Williams	0.27	0.03	
28	Terrance West	2.01	0.29	
29	Ben Tate	1.14	0.19	
30	Benny Cunningham	-1.72	-0.22	
31	Pierre Thomas	-1.42	-0.24	
32	Isaiah Crowell	-2.04	-0.25	
33	Khiry Robinson	-3.61	-0.6	
34	Bishop Sankey	0.85	0.11	
35	Zac Stacy	-1.6	-0.23	
36	Jonathan Stewart	1.93	0.32	
37	LeGarrette Blount	-1.64	-0.18	
38	Reggie Bush	3.57	0.59	
39	Toby Gerhart	-0.27	-0.04	
40	Carlos Hyde	0.65	0.08	
41	Theo Riddick	-0.38	-0.06	
42	Juwan Thompson	1.3	0.16	
43	Devonta Freeman	-1.29	-0.16	
44	Tre Mason	3.71	0.93	
45	Robert Turbin	-0.63	-0.08	
46	James Starks	0.22	0.03	
47	Doug Martin	-0.79	-0.16	
48	Travaris Cadet	1.07	0.13	
49	Shonn Greene	-2.98	-0.5	
50	Jacquizz Rodgers	-1.61	-0.2	

DPS Rankings - WR

Rank	Player	DPS	DPS Adjusted	(S)leeper/(D)ump
1	Antonio Brown	0.0	0.0	
2	Demaryius Thomas	4.01	0.5	
3	Jeremy Maclin	-0.61	-0.08	
4	Randall Cobb	-0.57	-0.07	
5	Jordy Nelson	3.18	0.4	
6	Emmanuel Sanders	-1.25	-0.16	
7	Dez Bryant	0.37	0.04	
8	Mohamed Sanu	-1.08	-0.14	
9	Golden Tate	-0.8	-0.1	
10	Steve Smith	-1.97	-0.22	
11	Julio Jones	7.81	0.98	
12	Sammy Watkins	0.0	0.0	
13	Kelvin Benjamin	0.0	0.0	
14	Terrance Williams	-2.85	-0.32	
15	Alshon Jeffery	1.35	0.17	
16	Allen Hurns	-6.92	-0.77	
17	Mike Wallace	-0.22	-0.03	
18	Mike Evans	-0.42	-0.06	
19	Torrey Smith	-1.26	-0.14	
20	Eric Decker	-0.77	-0.1	
21	Brandon Marshall	3.83	0.48	
22	Anquan Boldin	-0.79	-0.1	
23	Brandin Cooks	-0.51	-0.06	
24	Andre Holmes	-1.71	-0.21	
25	Larry Fitzgerald	1.01	0.13	
26	Kendall Wright	-2.58	-0.32	
27	Allen Robinson	-1.91	-0.21	
28	James Jones	-1.31	-0.16	
29	Roddy White	1.98	0.28	
30	Andrew Hawkins	-1.05	-0.13	
31	Vincent Jackson	3.19	0.4	
32	John Brown	-2.12	-0.26	
33	Michael Crabtree	0.15	0.02	
34	Steve Johnson	-2.75	-0.34	
35	Markus Wheaton	-1.95	-0.22	
36	A.J. Green	12.92	2.58	
37	Michael Floyd	2.78	0.35	
38	Jordan Matthews	-1.51	-0.19	
39	Rueben Randle	0.71	0.09	
40	Marques Colston	0.59	0.07	
41	Justin Hunter	0.45	0.06	
42	Taylor Gabriel	-1.56	-0.2	
43	Martavis Bryant	1.82	0.61	
44	Doug Baldwin	2.46	0.31	
45	Calvin Johnson	18.85	3.77	
46	Miles Austin	-3.2	-0.4	
47	Odell Beckham Jr.	2.62	0.65	
48	Percy Harvin	4.29	0.61	
49	Kenny Stills	0.73	0.1	
50	Kenny Britt	1.0	0.13	

DPS Rankings - TE

Rank	Player	DPS	DPS Adjusted	(S)leeper/(D)ump
1	Julius Thomas	0.0	0.0	
2	Greg Olsen	0.0	0.0	
3	Martellus Bennett	0.0	0.0	
4	Jimmy Graham	6.55	0.82	
5	Delanie Walker	-2.02	-0.25	
6	Travis Kelce	1.33	0.17	
7	Larry Donnell	1.06	0.13	
8	Jason Witten	0.44	0.05	
9	Owen Daniels	-0.85	-0.11	
10	Heath Miller	1.54	0.17	
11	Zach Ertz	0.25	0.03	
12	Charles Clay	-0.36	-0.05	
13	Lance Kendricks	-3.79	-0.47	
14	Scott Chandler	-0.7	-0.09	
15	Jace Amaro	-1.44	-0.16	
16	Jared Cook	1.13	0.14	
17	Mychal Rivera	0.41	0.05	
18	Jordan Cameron	-2.0	-0.33	
19	Clay Harbor	1.63	0.27	
20	Josh Hill	-3.78	-0.47	
21	Anthony Fasano	-4.72	-0.59	
22	Vernon Davis	4.46	0.74	
23	Gavin Escobar	-1.13	-0.13	
24	Andrew Quarless	1.06	0.13	
25	Jermaine Gresham	1.63	0.2	
26	John Carlson	0.8	0.1	
27	Jeff Cumberland	-0.24	-0.03	
28	Austin Seferian-Jenkins	1.38	0.23	
29	Jim Dray	-1.84	-0.23	
30	Levine Toilolo	-3.28	-0.41	
31	Jacob Tamme	0.0	0.0	
32	Cooper Helfet	0.0	0.0	
33	Eric Ebron	2.37	0.4	
34	Luke Willson	3.03	0.43	
35	Brandon Myers	0.54	0.07	
36	Crockett Gillmore	2.06	0.23	
37	Richard Rodgers	2.25	0.28	
38	Brent Celek	0.93	0.12	
39	Benjamin Watson	-0.6	-0.07	
40	Gary Barnidge	1.18	0.15	
41	Brandon Pettigrew	0.25	0.04	
42	Adrien Robinson	0.13	0.02	
43	Ed Dickson	-0.29	-0.03	