Use of Polynomial Regression in Fantasy Football Drafts

Quick Overview of Fantasy Football Draft

- In fantasy football, fantasy managers select NFL (National Football League) players to their Fantasy Team rosters
- A popular player selection methodology in fantasy football leagues is a fantasy football draft
- In a fantasy football draft, fantasy managers select from a pool of players, and once a player is selected, that player is no longer available to the other fantasy managers

League Scoring

- There are many different potential scoring systems in fantasy football
- Scoring can differ for different positions: RB, WR, TE, QB etc
    - For RB, WR, and TE
        - 1 per reception
        - 1 point per 10 yds gains
        - 6 points per Touchdown
        - Decimals Allowed
    - For QB
        - 4 points per passing TD
        - 6 points per rushing TD
        - 1 point per 25 yds gained passing
        - 1 point per 10 yds gained rushing

Project Topic

- Goal is it fit models to predict average points per game
    - Helps to make decisions and improve strategies for my upcoming draft
    - Helps provide a target for evaluating if a pick was good after the season
- Predict PPG based on where the player is draft
    - Typical measure is average draft position (ADP)
        - Changes in popular strategies affect where different positions are drafted over time.
            - For example, 6 of the top 10 picks this year, by ADP, are WRs, but only 1 of the first 10 picks was WR in 2021
            - How the fantasy football community values different positions over time changes
            - ADP is driven by professional fantasy analyst that treat fantasy football as a full time job. It is generally a pretty decent predictor of player performance
    - Positional ranking by ADP might be a better predictor of player performance

Data

- Data sourced from FantasyPros
  - Downloadable tabular data with a free subscription
    - PPG: https://www.fantasypros.com/nfl/reports/leaders/ppr.php?year=2023 (2016-2023)

	#	Player	Pos	Team	1	2	3	4	5	6	...	12	13	14	15	16	17	AVG	TTL	year	18
0	1.0	David Johnson	RB	FA	23.2	17.3	26.1	14.4	33.5	34.8	...	30.1	38.5	17.1	26.8	33.6	NaN	26.7	400.4	2017	NaN
1	2.0	Aaron Rodgers	QB	NYJ	23.6	17.4	26.4	-	15.9	12.5	...	23.1	16	21.2	12	37.2	NaN	23.1	345.8	2017	NaN
2	3.0	Ezekiel Elliott	RB	DAL	12.2	14.7	18	22.7	32.1	19.4	...	26	20.5	10.7	27.8	22.2	NaN	21.7	325.4	2017	NaN
3	4.0	Matt Ryan	QB	FA	24.4	27.8	19.9	35.5	15	21.6	...	18.3	16.2	21.5	19.3	20	NaN	21.2	318.0	2017	NaN
4	5.0	Le'Veon Bell	RB	FA	-	-	-	22.8	24.4	18.8	...	24.2	22.2	51.8	18.1	28.7	NaN	26.5	317.4	2017	NaN

    - ADP: https://www.fantasypros.com/nfl/adp/ppr-overall.phpf (2017-2024)

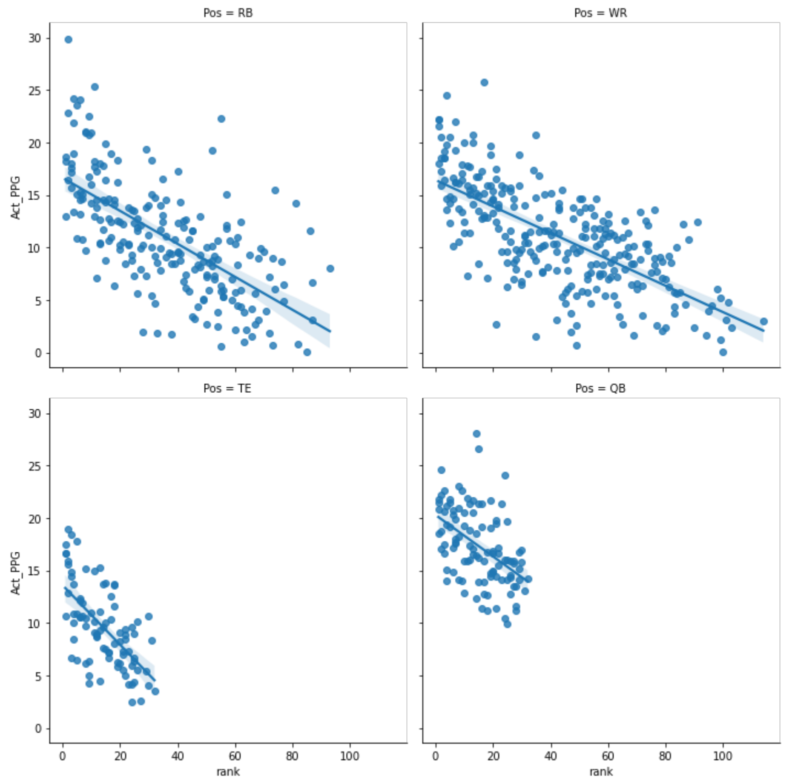
Rank	Player	Team	Bye	POS	ESPN	Sleeper	NFL	RTSports	FFC	AVG
1.0	David Johnson	NaN	NaN	RB1	1.0	NaN	NaN	NaN	NaN	1.0
2.0	Le'Veon Bell	NaN	NaN	RB2	2.0	NaN	NaN	NaN	NaN	2.0
3.0	Antonio Brown	NaN	NaN	WR1	3.0	NaN	NaN	NaN	NaN	3.0
4.0	Julio Jones	NaN	NaN	WR2	4.0	NaN	NaN	NaN	NaN	4.0
5.0	Odell Beckham Jr.	MIA	1	WR3	5.0	NaN	NaN	NaN	NaN	5.2

Data Continued

- After merging PPG to ADP, there were several missing values for PPG at high ADP
  - These were likely all zero
  - Since it is highly unlikely that a player with an ADP > 250 would be drafted in my league, they were removed from the data
  - Also removed QBs and TE with a positional ranking > 32 since there are only 32 NFL teams
  - There were still still about 225 cases out of 1,550 records with no PPG corresponding to the ADP. They were mostly concentrated in the earlier years. So, they were removed as well
  - Also, removed players with a PPG of zero. Some players were injured right before the start of the season, and I didn't want them included in the model, leaving 1,319 usable records.
- Split into 4 different training and 4 test sets
    - WR,RB,TE, and QB modeled separately
    - Training: 2017, 2018, 2019, 2021
    - Testing: 2022 and 2023

Simple Linear Relationship between Positional Rank and PPG

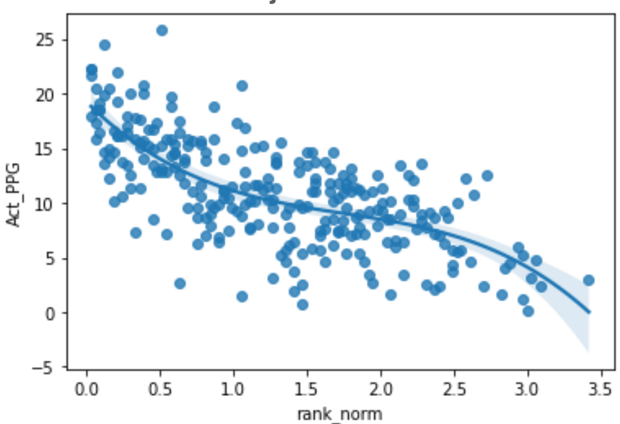
There is a linear relationship between ‘rank’ and PPG (Fantasy Points Per Game)



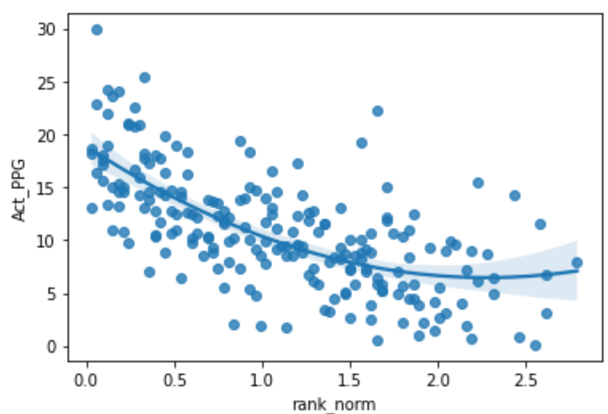
Final Model - Polynomial Regression

There is a stronger polynomial relationship between ‘rank’ and PPG

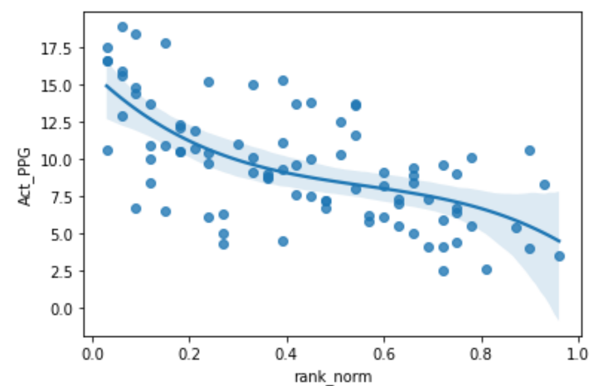
WR Model
Degree = 3
Adj. R2 =0.503



RB Model
Degree = 2
Adj. R2 =0.464



TE Model
Degree = 3
Adj. R2 =0.433



Performance on the Testing Data

- Fit the model to each position group individually and combined into one to measure performance
- Calculated R-Squared, MAE, MAPE, MSE, RMSE on testing data and training data for both the polynomial regression model (“complex”) and the simple regression model (“simple”)

Data_Model	r_squared	mae	mape	mse	rmse
test_complex	0.58	2.8	0.51	12.0	3.46
test_simple	0.57	2.8	0.5	12.38	3.52
train_complex	0.57	2.74	0.56	12.32	3.51
train_simple	0.54	2.84	0.52	13.19	3.63

- The QB model was a simple regression model. No polynomial model fit well. Below are results when only looking at RB, WR, and TE

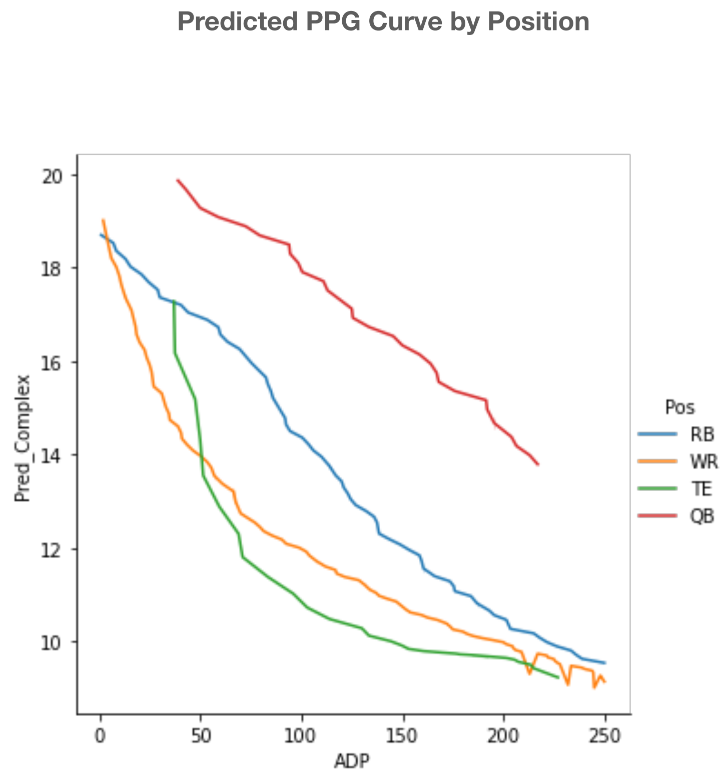
Data_Model	r_squared	mae	mape	mse	rmse
test_no_qb_complex	0.51	2.8	0.56	11.93	3.45
test_no_qb_simple	0.49	2.8	0.55	12.35	3.51
train_no_qb_complex	0.49	2.78	0.64	12.71	3.56
train_no_qb_simple	0.45	2.91	0.59	13.75	3.71

Final Cheat Sheet — 2024

Top 20 Picks by ADP

Player	Team	ADP	rank	Pos	PPG	Med_PPG	Pred_Complex
Christian McCaffrey	SF	1	1	RB	24.5	22.55	**19**
CeeDee Lamb	DAL	2	1	WR	23	18.9	**19**
Tyreek Hill	MIA	3	2	WR	23.7	25.4	**19**
Ja'Marr Chase	CIN	4	3	WR	17.1	12.1	**19**
Justin Jefferson	MIN	5	4	WR	18.5	24	**18**
Amon-Ra St. Brown	DET	6	5	WR	20.2	19.6	**18**
Bijan Robinson	ATL	7	2	RB	13.8	12.6	**19**
A.J. Brown	PHI	8.5	6	WR	18.1	17.55	**18**
Breece Hall	NYJ	8.5	3	RB	16.3	13.8	**18**
Puka Nacua	LAR	10	7	WR	17.8	18.7	**18**
Garrett Wilson	NYJ	11	8	WR	13	14.7	**18**
Jahmyr Gibbs	DET	13	4	RB	16.7	14.9	**18**
Drake London	**ATL**	**13**	**9**	**WR**	**11.1**	**10.5**	**17**
Marvin Harrison Jr.	**ARI**	**13**	**10**	**WR**	**NaN**	**NaN**	**17**
Jonathan Taylor	IND	15.5	5	RB	14.3	14.5	**18**
Nico Collins	**HOU**	**16**	**11**	**WR**	**16.1**	**13.9**	**17**
Chris Olave	**NO**	**17**	**12**	**WR**	**14.4**	**16.6**	**17**
Davante Adams	**LV**	**18**	**13**	**WR**	**15.6**	**12.65**	**17**
Deebo Samuel Sr.	**SF**	**18.5**	**14**	**WR**	**17**	**17.05**	**17**
Jaylen Waddle	MIA	20	15	WR	14.2	12.35	**16**

Predicted PPG Curves



Predicted PPG Counts

Predicted PPG Counts by Position