

# Predicting NBA Player FanDuel Score

By: Dong Zhen





## About this project.

### What is FanDuel?

A sports focused gambling website that offers sportsbook, daily fantasy, and horse race betting

### Objective

Help daily fantasy basketball betting group place in the top 23% **by predicting NBA players' score in FanDuel**

FanDuel's  
point  
system.

FD Basketball Scoring as of 5/6/2021

FGM	FTM	3PM	REB	AST	STL	BLK	TO
2	1	1	1.2	1.5	3	3	-1

	FGM	FTM	3PM	REB	AST	STL	BLK	TO
<b>Russell Westbrook</b>	13	6	0	11	4	4	0	5
<b>FanDuel Score</b>	26	6	0	13.2	6	12	0	-5

Total Points: **58.2**

# 2017 - 19 NBA Data.

## Players

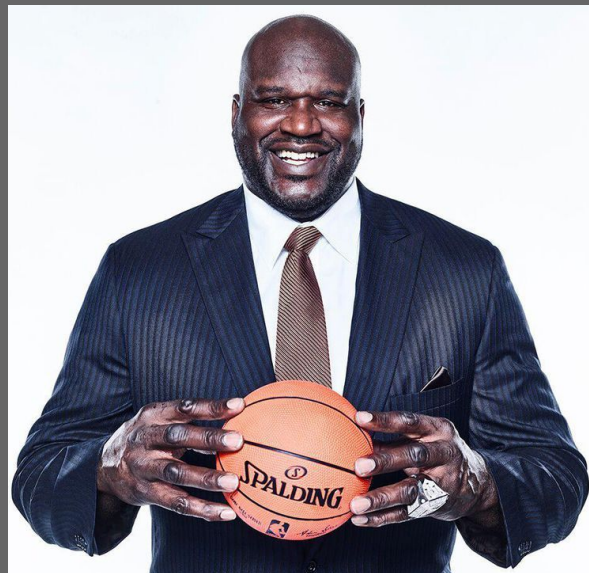
- ❑ List of players
- ❑ Minimum of 30 games a season
- ❑ Minimum 15 minutes per game

## Teams

- ❑ NBA team rosters
- ❑ Team statistics

Why  
2017-19?

Centers Dominate



Guards Dominate

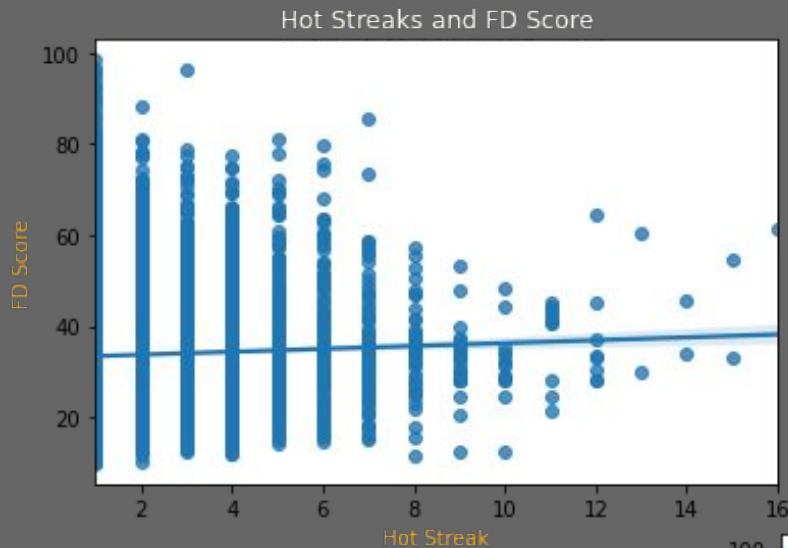


# Generalizing FD Score.

Player tendencies + Player attributes +  
Momentum + Opponent's defensive  
tendencies = **FD Score**

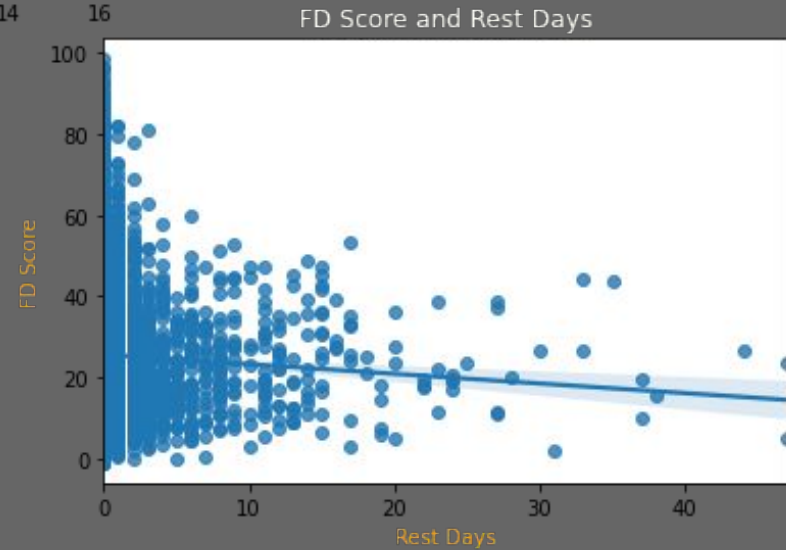
- ❑ Offensive activity example: FG
- ❑ Defensive activity example: fouls

# Feature Designing.

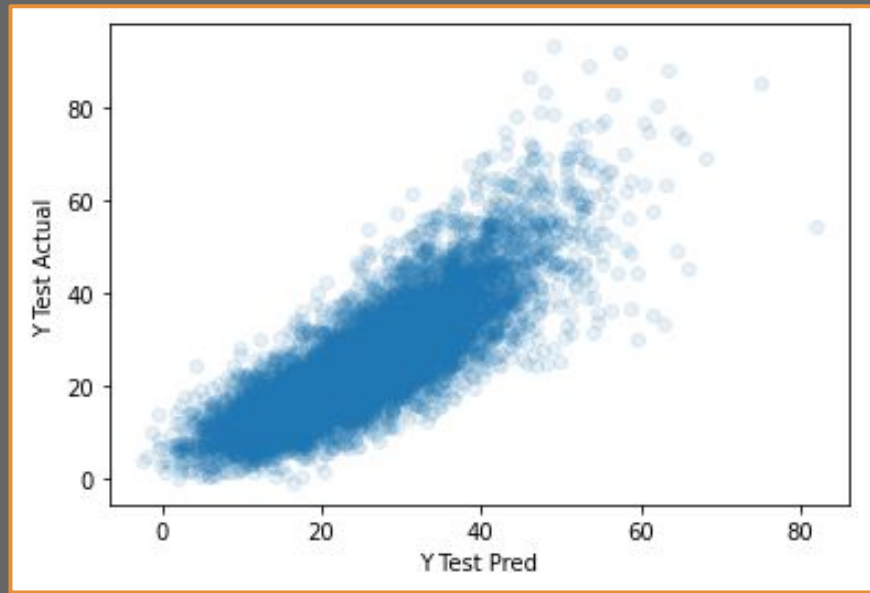


**Hot streaks** indicate momentum

**Rest days** are measured by number of games between previous and current



# Using Linear Regression.



Training  $R^2$  Score: 0.6850205173145631

Training RMSE: 7.256913673779181

Training MAE: 5.590420023489153

Test  $R^2$  Score: 0.6844943075416979

Test RMSE: 7.256913673779181

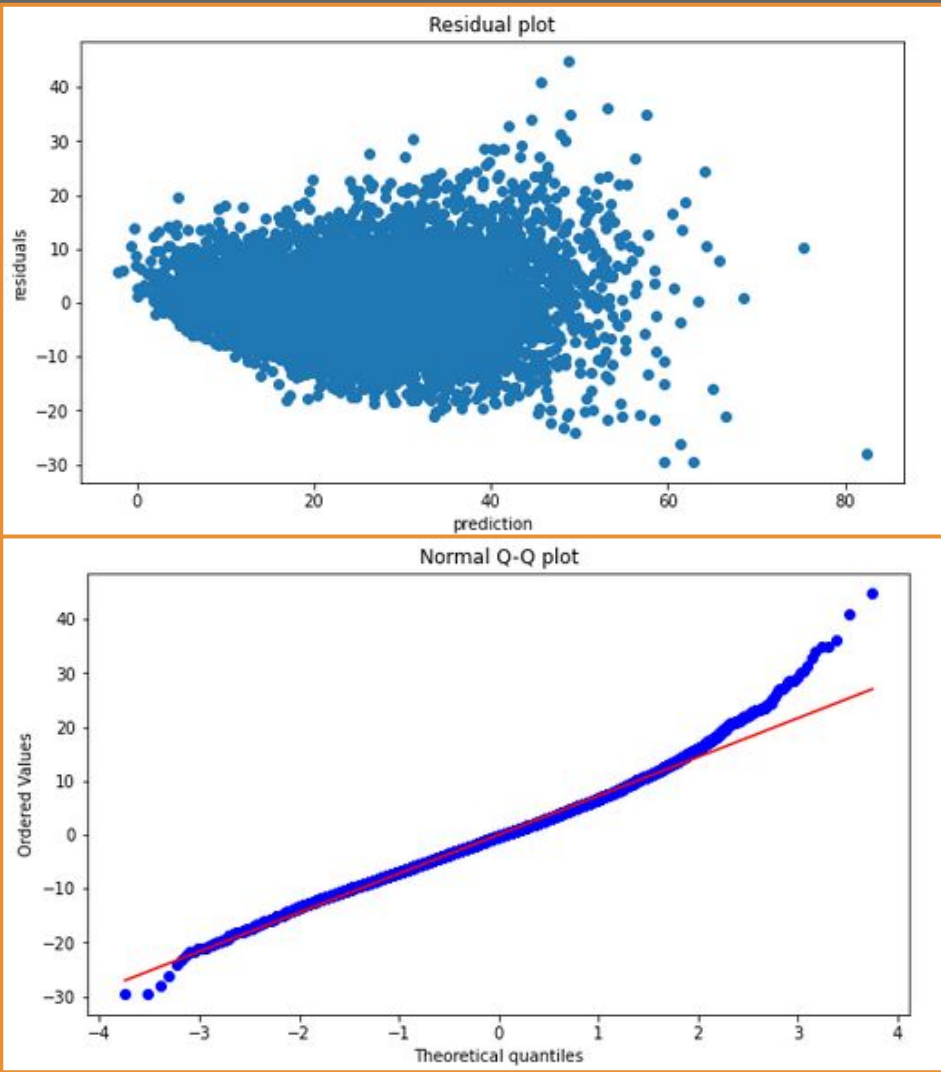
Test MAE: 5.614603579545828

Cross validation scores : [0.68404225 0.68644522  
0.67033296 0.68906962 0.69267176]

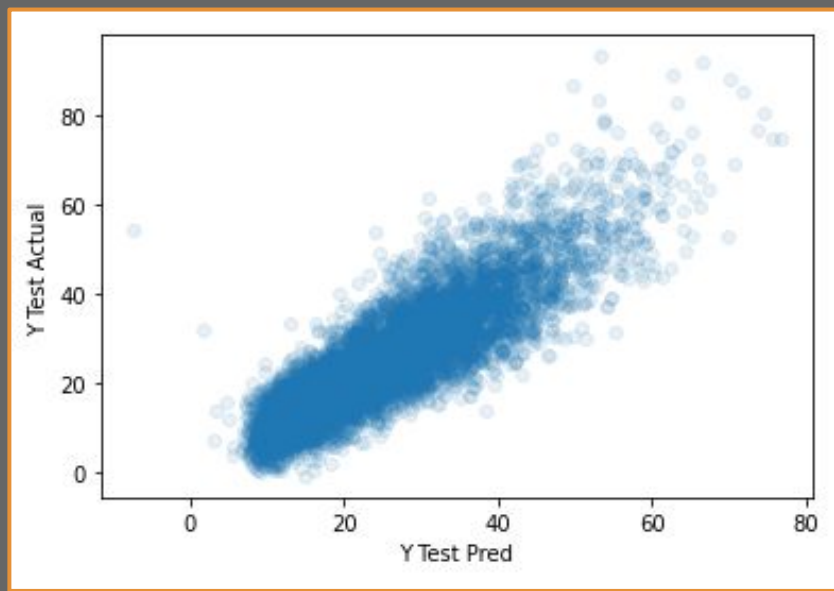
Cross validation scores : 0.6845123609680444



# Checking for OLS Assumptions



## Polynomial to the second degree



Training  $R^2$  Score: 0.751815672294646

Training RMSE: 6.441663002232507

Training MAE: 4.909333544347451

Test  $R^2$  Score: 0.7436806607768427

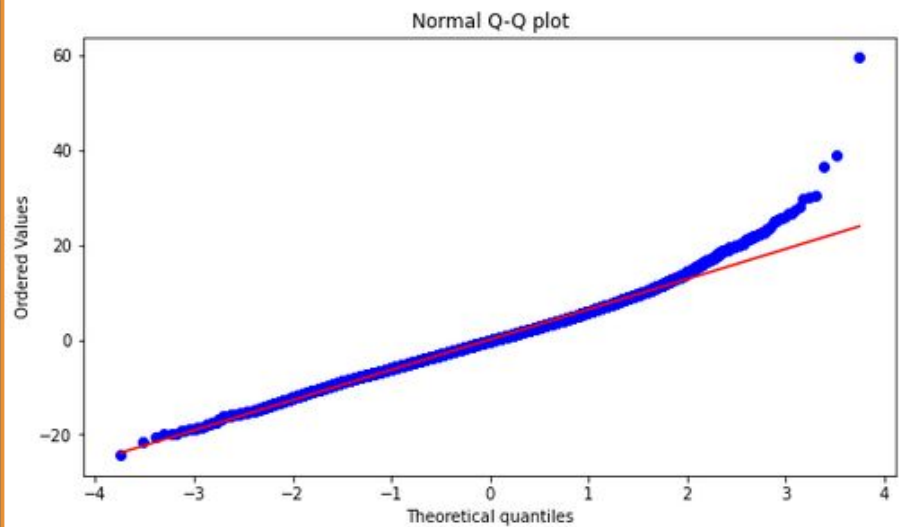
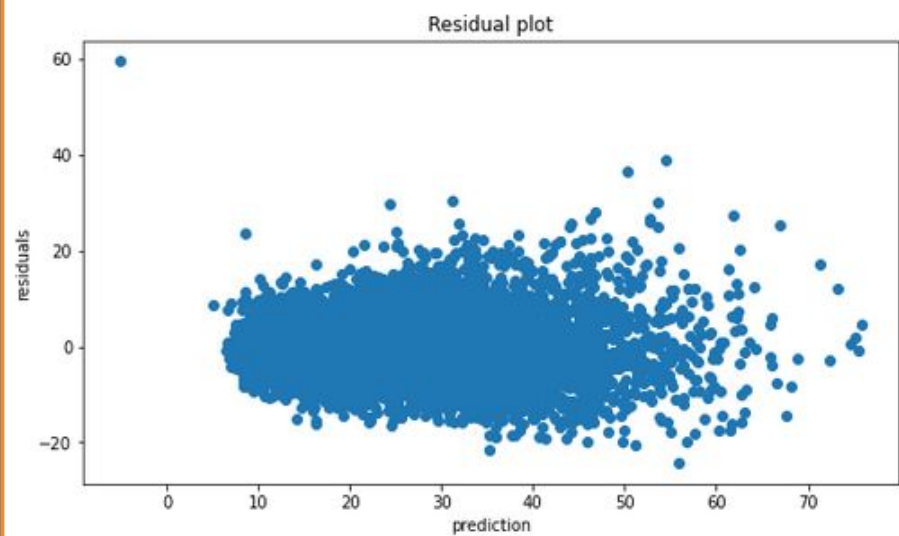
Test RMSE: 6.441663002232507

Test MAE: 5.031599774824723

Cross validation scores: [0.74790621 0.74734498  
0.74166187 0.74022639 0.75743132]

Cross validation scores: 0.7469141550672334

# Residuals Improvement.



# Prediction.

This was a really close prediction without any of the changes that I made

```
test_df2 = fds_df.sample(random_state = 7490)
test_df2.head()
```

	Date	Age	Name	Team	Opp	Minutes Played	Personal Fouls	Rest Days	FD Score	FGA/M	...	Weight	Exp	Opp_Avg_Pace	Opp_Avg_Off_Rtg	Opp_Avg_Def_Rtg	Games Started Starter	Position_PF	Posit
18639	2018-01-19	28	Markieff Morris	WAS	DET	31.55	4	0	31.8	0.44374	...	245.0	6.0	96.2	107.2	107.3	1	1	

1 rows × 25 columns

```
test_df_f2 = test_df2[['Age', 'Minutes Played', 'Personal Fouls', 'Rest Days', 'FGA/M',
                        'Hot Streak', 'Prev FD Score', 'Weight', 'Exp', 'Opp_Avg_Pace',
                        'Opp_Avg_Off_Rtg', 'Opp_Avg_Def_Rtg', 'Games Started Starter',
                        'Position_PF', 'Position_PG', 'Position_SF', 'Position_SG']]
```

```
test_df_f2.head()
```

	Age	Minutes Played	Personal Fouls	Rest Days	FGA/M	Hot Streak	Prev FD Score	Weight	Exp	Opp_Avg_Pace	Opp_Avg_Off_Rtg	Opp_Avg_Def_Rtg	Games Started Starter	Position_PF	Position_PG	Position_SF	Positior
18639	28	31.55	4	0	0.44374	1	8.5	245.0	6.0	96.2	107.2	107.3	1	1	0	0	

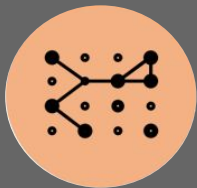
```
lm.predict(test_df_f2)
```

```
array([[30.8207839]])
```

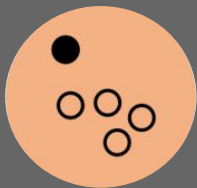
```
test_df_t2 = test_df2['FD Score']
test_df_t2
```

```
18639    31.8
Name: FD Score, dtype: float64
```

## Future Work.



Add more **complexity**, use Selenium to get important per game player and opponent tendencies



Look into what is causing the **outliers**



Incorporate **FD salary** to help client make the best budget picks