



# Best NBA Players, Value for Money

Web Scrapping and Linear Regression Project to Predict Salaries

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# Introduction

Question :

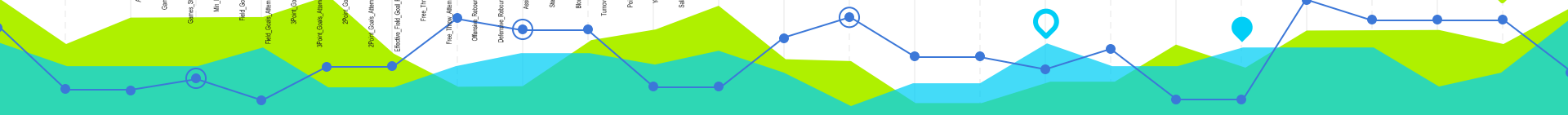
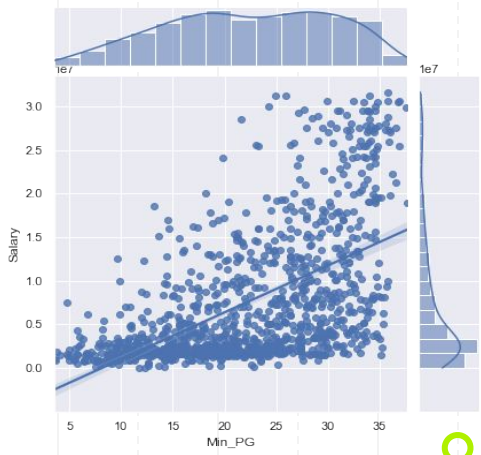
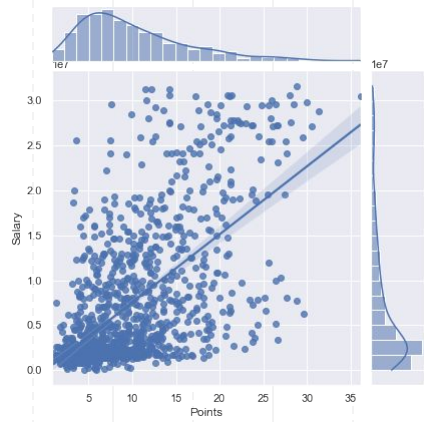
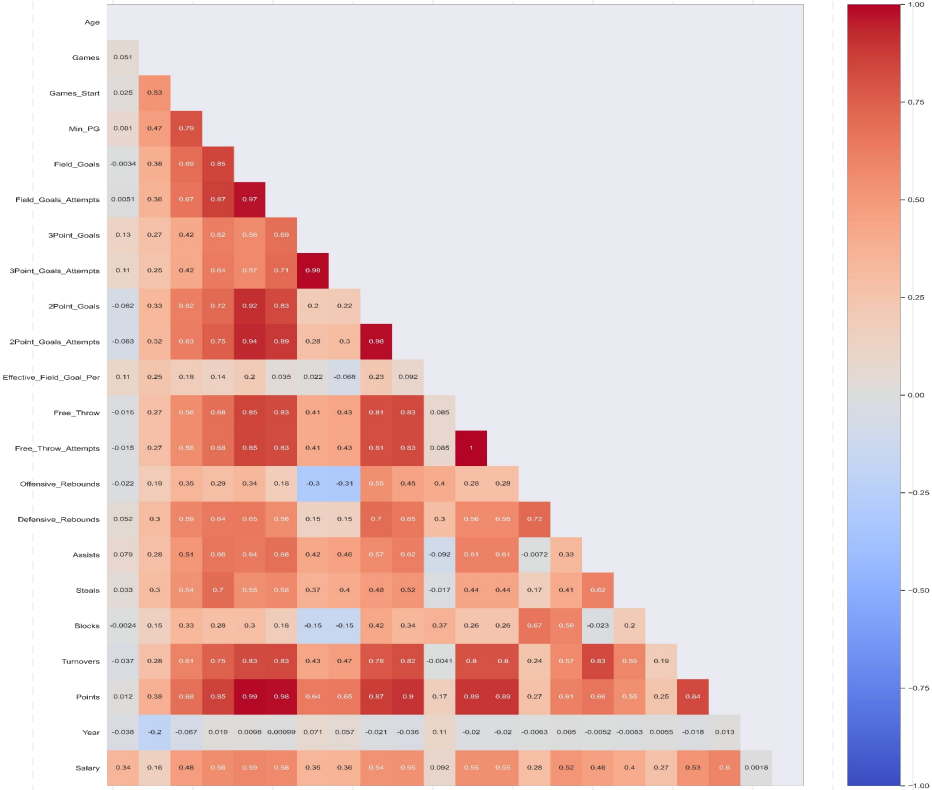
*Discover 10 most underpaid NBA players*

Data :

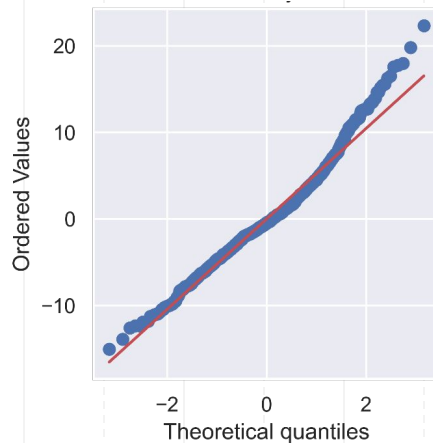
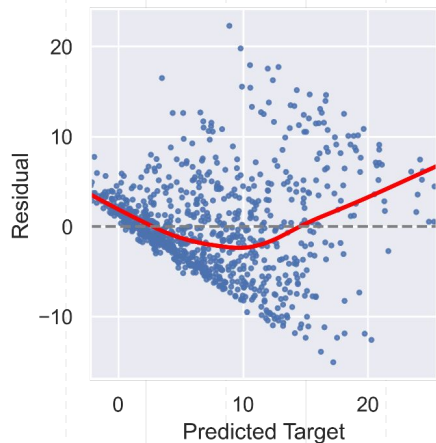
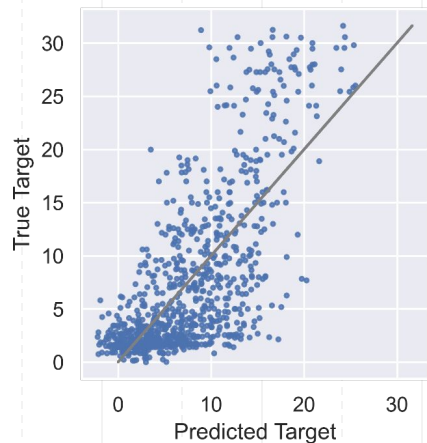
- ➔ <https://www.basketball-reference.com/>
- ➔ annual salaries and more than **20 per game statistics** for more than **400 players**
- ➔ Season 2019, 2020 and 2021



# Data



# Linear Regression



Notes from initial model:

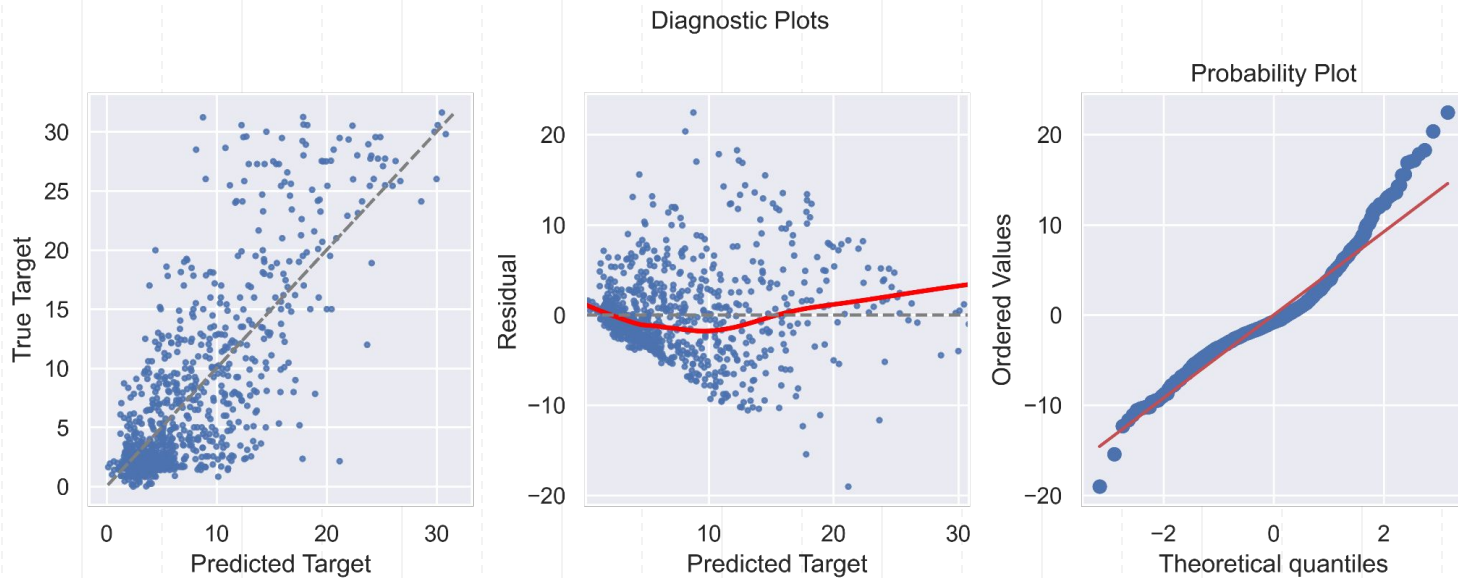
- Skewed target variable
- Outliers
- Under and overfitting
- Polynomial trend

Linear Regression	
$R^2$ Train	$R^2$ Test
0.53	0.56

0.7% improvement in MAE

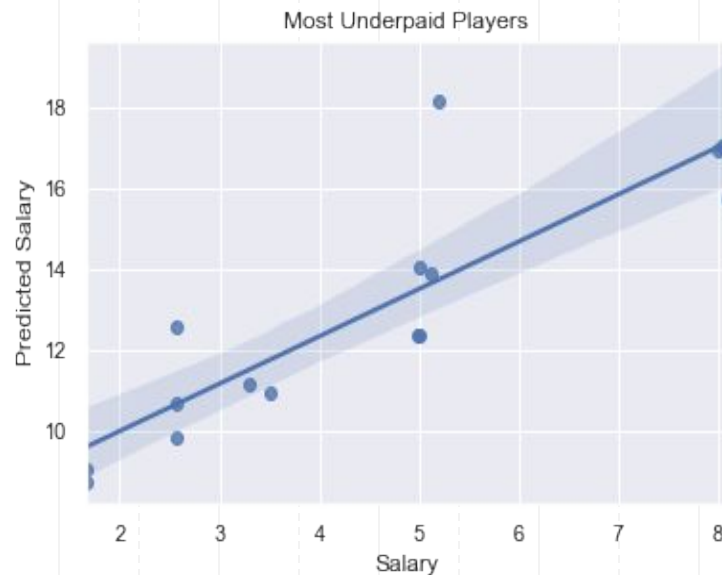
Poly(degree = 2), LASSO	
$R^2$ Train	$R^2$ Test
0.61	0.60

# Polynomial transformation (degree = 2), LASSO



# 10 Top Underpaid Players

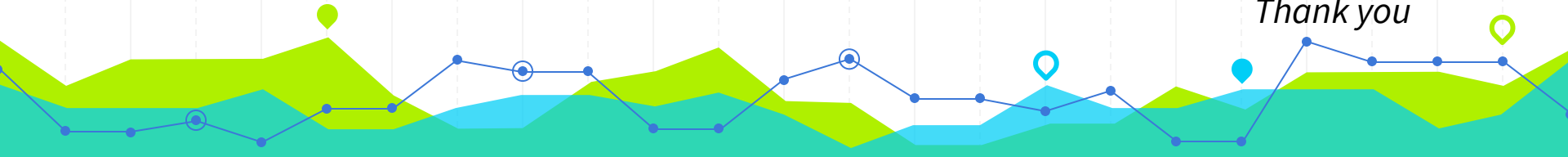
Name	Salary(in Million)	Predicted	95% CI Upper Limit	NBA Draft
Donovan Mitchell	\$5.20	\$18.18	\$27.46	2017
<b>Enes Kanter</b>	<b>\$5.01</b>	<b>\$14.06</b>	<b>\$23.34</b>	<b>2011</b>
Luka Dončić	\$8.05	\$17.07	\$26.35	2018
<b>Mason Plumlee</b>	<b>\$8.00</b>	<b>\$16.97</b>	<b>\$26.25</b>	<b>2013</b>
Bam Adebayo	\$5.12	\$13.90	\$23.18	2017
<b>Jeff Green</b>	<b>\$2.56</b>	<b>\$10.72</b>	<b>\$20.00</b>	<b>2007</b>
<b>Michael Carter-Williams</b>	<b>\$3.30</b>	<b>\$11.20</b>	<b>\$20.48</b>	<b>2013</b>
De'Aaron Fox	\$8.10	\$15.74	\$25.02	2017
Derrick White	\$3.52	\$10.98	\$20.26	2017
Kendrick Nunn	\$1.66	\$9.09	\$18.37	2018



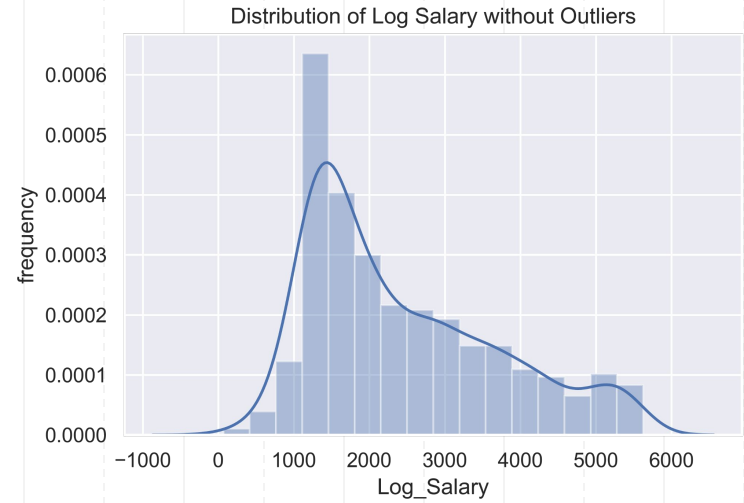
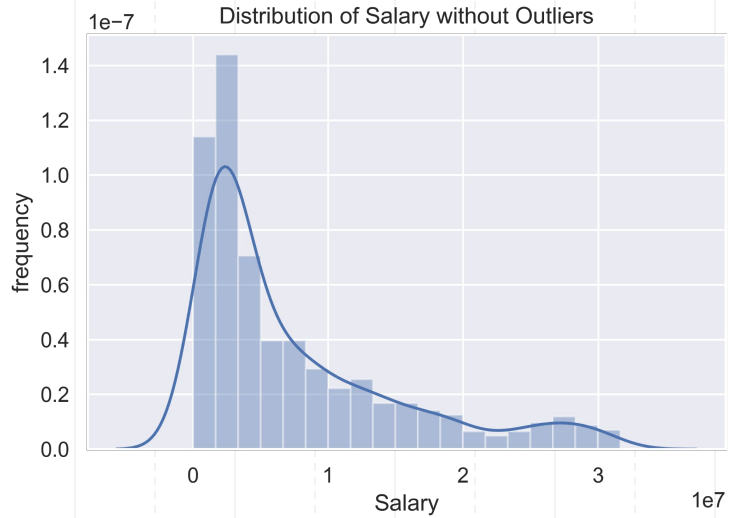
# Future Works

- Add more metrics to describe a player's performance: injuries, years of experience.
- Add more features that might indirectly affect salaries: team market size, expected fan-based revenue, merchandising and advertising.
- Apply different models: Decision Tree Regressor, Random Forest Regressor, Gradient Boosted Tree Regressor.
- Apply deeper feature selection to simplify the model without losing the prediction power.

*Thank you*

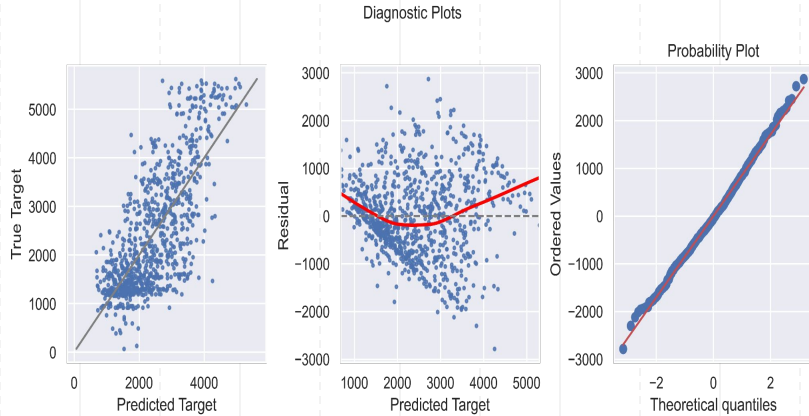


# The Distribution of Salary

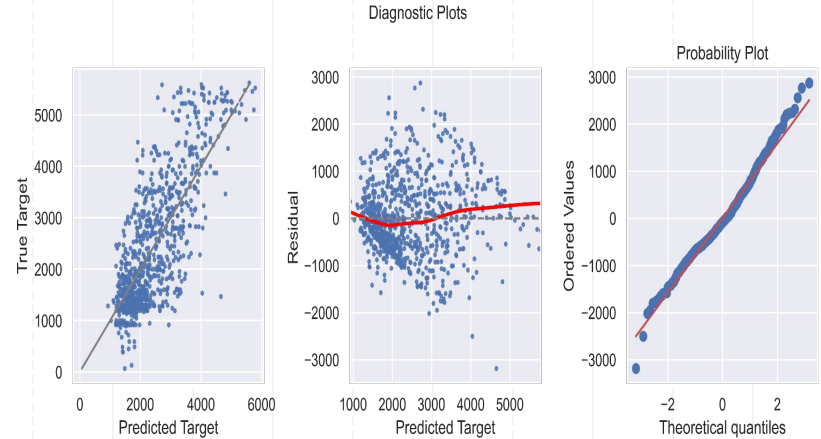




# Linear Regression with Log Salary



Linear Reg-Log Salary	
$R^2$ Train	$R^2$ Test
0.55	0.57



Poly(degree = 2), LASSO- Log Salary	
$R^2$ Train	$R^2$ Test
0.61	0.58