# **STAT 596 : Regression and Time Series Analysis** FINAL PROJECT PRESENTATION

**NBA Salary Insights** 

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### **Background and Goals**

- Identify **factors affecting** the player Salaries.
- **Leveraging player stats** and demographics across various teams, their positions, shooting styles, etc over the period of time.
- Performed Forward Selection and Backward Elimination using AIC and BIC values for parameter selection.
- Linear **Hypothesis testing** for our Linear Models.
- Predicting Salaries for NBA players by fitting a Linear Model.

#### **Data Set**

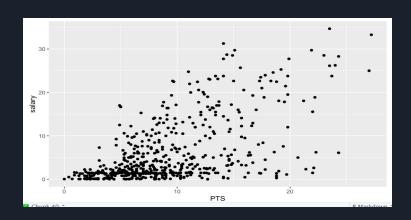
- NBA **Player Statistics** data.
- NBA **Player salaries modelling** for season 2014-15
- Data sets sources: Players.csv and salaries.csv
- Players.csv: Player demographics and Statistics
- Salaries.csv: Salaries over the period of time (1985-2018)

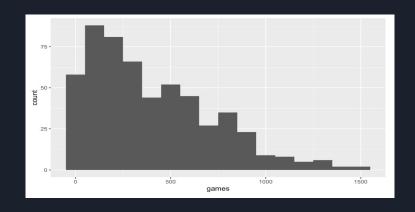
### **Data Manipulation**

- Unified the dataset using player\_id as key merging players.csv and salaries.csv.
- Filled up missing values in the data set.
- Handled categorical variables in the data set to fit our linear model.
- Normalized Target variable "salary" in the range of millions to user friendly variable.
- **Created new columns** for age at the end of season, height in cm, weight, etc.

## **Exploratory Data Analysis**

#### Univariate Analysis





**Scatter Plot**: Points scored vs Salary

**Histogram**: No of Games played

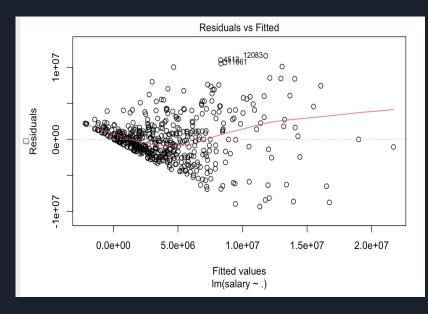
## **Exploratory Data Analysis**

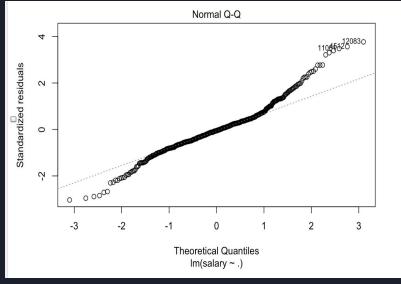
#### Multicollinearity

	age	AST	FG	FG3	FT	games	
age	1.0000000000	0.23176645	0.09090559	0.098598622	0.172397637	0.81638598	
AST	0.2317664524	1.00000000	-0.05612518	0.244184105	0.228739757	0.39810739	
FG	0.0909055860	-0.05612518	1.00000000	-0.226472591	-0.178475353	0.21365929	
FG3	0.0985986223	0.24418411	-0.22647259	1.000000000	0.330818851	0.13144822	
FT	0.1723976365	0.22873976	-0.17847535	0.330818851	1.000000000	0.20396056	
games	0.8163859761	0.39810739	0.21365929	0.131448220	0.203960563	1.00000000	
PER	0.2597386765	0.39308625	0.69047200	-0.010543621	0.118698026	0.47895319	
PTS	0.2842778540	0.63666352	0.19945118	0.253809447	0.317624182	0.57417772	
TRB	0.1660983406	0.12714491	0.55301395	-0.181325971	-0.135426180	0.40120882	
WS	0.6467375623	0.46202683	0.25998987	0.062398226	0.155952532	0.83968444	
eFG	0.0882649151	-0.04759632	0.86069735	0.117402814	-0.008211145	0.19210296	
height	-0.1055221519	-0.52748851	0.43816505	-0.371729580	-0.272720738	-0.03860283	
position	0.1033509758	-0.10783072	-0.33197041	0.347958886	0.134588731	0.10047067	
shoots	-0.0380478168	-0.09425524	-0.08581791	0.028789656	0.027476516	-0.07971788	
weight	0.0165369670	-0.41335617	0.43822076	-0.375919026	-0.257100978	0.08365706	
team	0.0006707831	0.01839429	0.04681294	-0.007403481	-0.053002423	0.03056276	
	PER	PTS	TRB	ws	eFG	height	
age	0.25973868 0	.2842778540	0.16609834	0.646737562	0.088264915	-0.105522152	
AST	0.39308625 0	.6366635188	0.12714491	0.462026828	-0.047596320	-0.527488506	
FG	0.69047200 0	.1994511838	0.55301395	0.259989869	0.860697355	0.438165050	
FG3	-0.01054362 0	. 2538094465	-0.18132597	0.062398226	0.117402814	-0.371729580	
FT	0.11869803 0	.3176241823	-0.13542618	0.155952532	-0.008211145	-0.272720738	
games	0.47895319 0	.5741777233	0.40120882	0.839684436	0.192102961	-0.038602826	
PER	1.00000000 0	.7019886500	0.67981745	0.622883120	0.590810290	0.193216934	
PTS	0.70198865 1	.0000000000	0.55823654	0.683043476	0.210252630	-0.097353385	
TRB	0.67981745 0	.5582365429	1.00000000	0.532154899	0.374209135	0.506925980	
WS	0.62288312 0	.6830434758	0.53215490	1.000000000	0.203844341	0.038856563	
eFG	0.59081029 0	.2102526299	0.37420914	0.203844341	1.000000000	0.262726567	
height	0.19321693 -0	.0973533850	0.50692598	0.038856563	0.262726567	1.000000000	
position	-0.26206423 0	.0477374904	-0.19798477	-0.005197819	-0.114141109	-0.094468250	
shoots	-0.14167976 -0	.1132685847	-0.11843646	-0.074815278	-0.059279446	0.002968970	
weight	0.27429812 -0	.0001830801	0.56071078	0.159940491	0.252361052	0.811746460	
team	0.03851069 0	.0153304730	0.01463674	0.010995065	0.038753088	0.004541374	
	position	shoots	weight	t ted	am		
age	0.103350976 -	0.03804782	0.0165369670	0.000670783	31		
Chunk 41							D. Manufadania

## **Linear Regression Models**

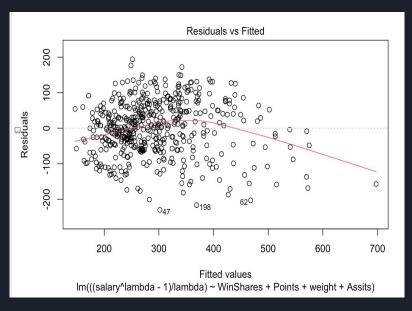
Initial Model: Linear model fitted on all parameters.

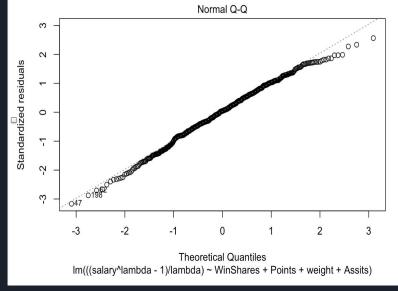




## **Linear Regression Models**

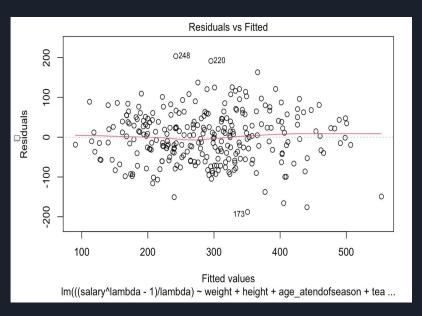
**Intermediate Model**: Linear model fitted on WinShares, Points Scored, Weight and Assists.

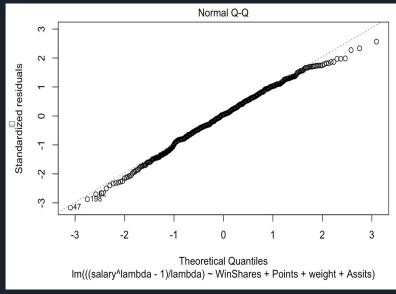




## **Linear Regression Models**

**Accepted Model**: Improved the intermediate model by **removing the outliers.** 





## **Model Performances**

Models	R Squared Values	Shapiro - Wilk Test(wilk normality Test) p values	Durbin Watson Test(Variance Test)
Initial Model	0.5779	4.285e-10	0.761
Intermediate Model	0.5341	0.02219	0.1354
Accepted Model	0.6651	0.704	0.7627

#### Conclusion

- We think that the analysis we performed on the players' on court performances with respect to their salaries has a major significance in potentially determining player contracts.
- However, there are far too many immeasurable qualities a player has that data alone cannot capture.
- Things like being a popular player for the team could significantly boost jersey sales even though they may not be performing as well as everyone else on the court isn't taken into account in our analysis.
- Even though a player isn't performing as good as he used to, he clearly has a use within the team to help everyone get better in practice and helping rookies and younger players develop their skills.

Anything more you wanted to see?