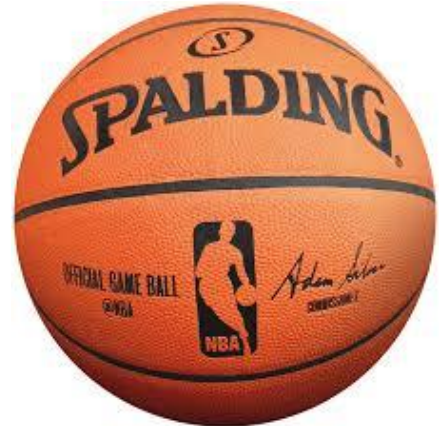


# NBA Player Retirement Prediction

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# **Problem**

**How accurately can we predict  
when NBA players will retire?**

# Goals and Relevance:

Goals:

- Predict **career length**
- Predict **retirement age**

Relevance/Interest:

- Basketball is among the top 3 watched sports in America
- There is a lot of recorded basketball data/stats(good dataframes to work with)
- We both enjoy watching the NBA

# Steps:

- Data Cleaning
- Preparing the data
- Modeling
- Loss analysis
- Results

# Dataset

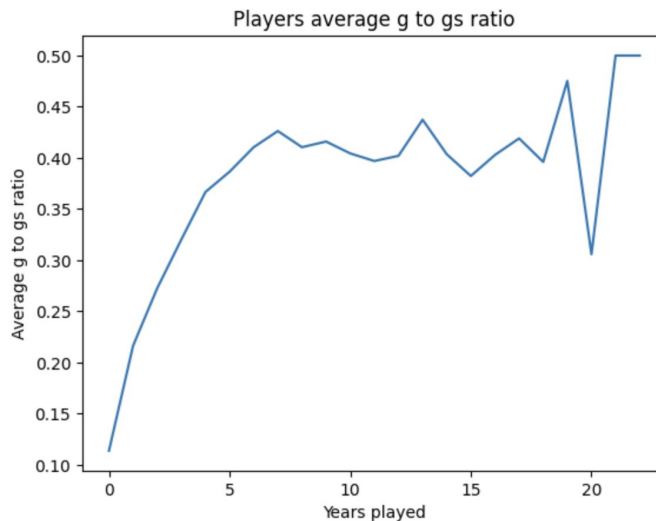
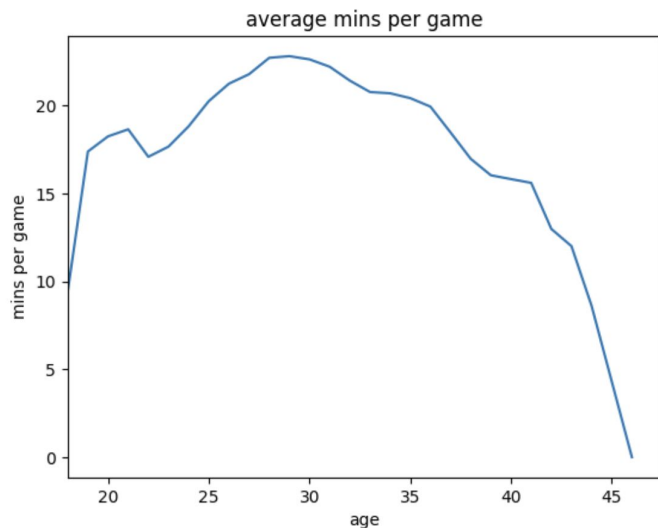
- The datasets we used are from [Kaggle](#)
- **Important column info:**
  - player, playerId, mp, g, gs, fg, fga, fg\_percent, 'x3p', 'x3pa', 'x3p\_percent', 'x2p', 'x2pa', 'x2p\_percent', 'e\_fg\_percent', 'ft', 'fta', 'ft\_percent', 'height', 'weight', 'num\_injuries'
- **Important row info:**
  - The original dataset **contains** rows for each unique data piece per player per season(ex: there are two different rows, within the same year, for a player who played for two different teams in the same season)

# Data Cleaning

- Merging:
  - **Merge multiple player stats datasets together** on the player\_id column(shared col across the main player stats datasets)
  - Include additional data sets that include **height/weight** information
  - Include a dataset with **injury data**(between the years of 2010-2020)
- Cleaning/deletion:
  - Create a filtered DF, **only including rows between 1947-2025**
  - **Replace missing data with Nan** to start with(later on we replace with mean col values)
- Create a column for:
  - **Retirement year**(last year played by a player)
  - **Career length**(count number of unique seasons)

# Initial Plotting

We made a few **initial plots** that we thought might show interesting relationships:



# Preparing Data for Modeling

- Only use the data from retired players(exclude active players)
- **Groupby playerId:**
  - **Each player** should have only a **single row**
  - The numeric columns are each **averaged across all seasons played**
  - Include a column that shows the **true retirement age**
  - Include a column that shows the **true career length**
  - Include the player and pos columns
  - Include height, weight, and injuries columns for applicable players
- Split the data into a train and test set (test size = 0.2)



# Modeling

- Create a **multiple linear regression model** function to predict the retirement age and the career length for each retired player
- Training data with features(x) and true values(y) used for fitting model
- Feature columns include FG%, MP, Height, Number of injuries
- Test data used to evaluate predictions
- Fill in missing values with the column mean because not too many missing values

# Modeling

**Results of calling the predictor function** and passing in the features and y arrays. We are using the feature(cols) to predict the **retirement age**. So we are running multiple linear regression to determine how accurately we can predict retirement age.

	player	retirementAge	predictedRetirementAge
0	0	0.0	24.625370
1	Alaa Abdelnaby	26.0	27.195733
2	Kareem Abdul-Jabbar	41.0	36.630127
3	Walt Hazzard	31.0	31.162181
4	Mahmoud Abdul-Rauf	31.0	31.112303
5	Tariq Abdul-Wahad	28.0	28.265437
6	Zaid Abdul-Aziz	31.0	27.900310
7	Shareef Abdur-Rahim	31.0	35.536842
8	Tom Abernethy	26.0	27.270291
9	Forest Able	24.0	23.996286
10	John Abramovic	28.0	26.671437
11	Álex Abrines	25.0	28.256299
12	Alex Acker	26.0	24.338062
13	Don Ackerman	23.0	24.857912
14	Mark Acres	30.0	28.604436
15	Bud Acton	26.0	24.316645
16	Quincy Acy	28.0	27.563520
17	Alvan Adams	33.0	32.958187
18	Don Adams	29.0	30.802637
19	George Adams	25.0	28.482041

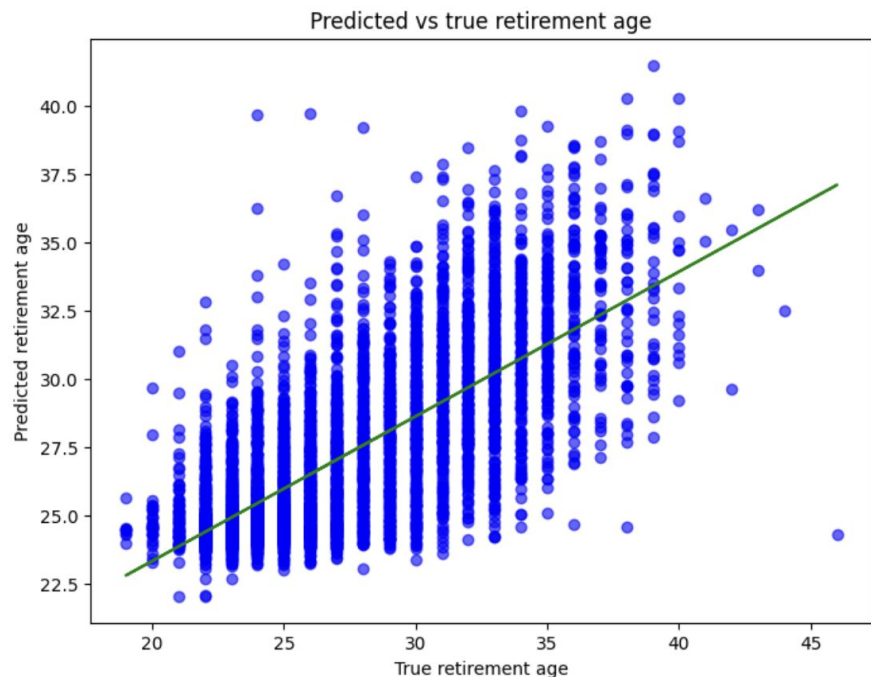
# Modeling

Results of calling the predictor function and passing in the x and y arrays. We are using the feature(cols) to predict the **career length**.

	career_length	predicted_career_length
1149	11.0	9.488108
393	10.0	6.830872
1268	4.0	4.904366
4233	2.0	3.101261
4181	10.0	9.799169
2680	14.0	10.059506
3949	16.0	9.190214
4854	2.0	0.575836
3757	1.0	3.047487
3979	6.0	8.312091
3418	4.0	4.275128
2509	2.0	4.041470
1371	1.0	0.591065
3478	2.0	1.791224
4748	7.0	4.791690
2577	16.0	14.496677
538	7.0	8.370778
718	1.0	2.636539
4502	16.0	9.897090
4473	2.0	0.558572

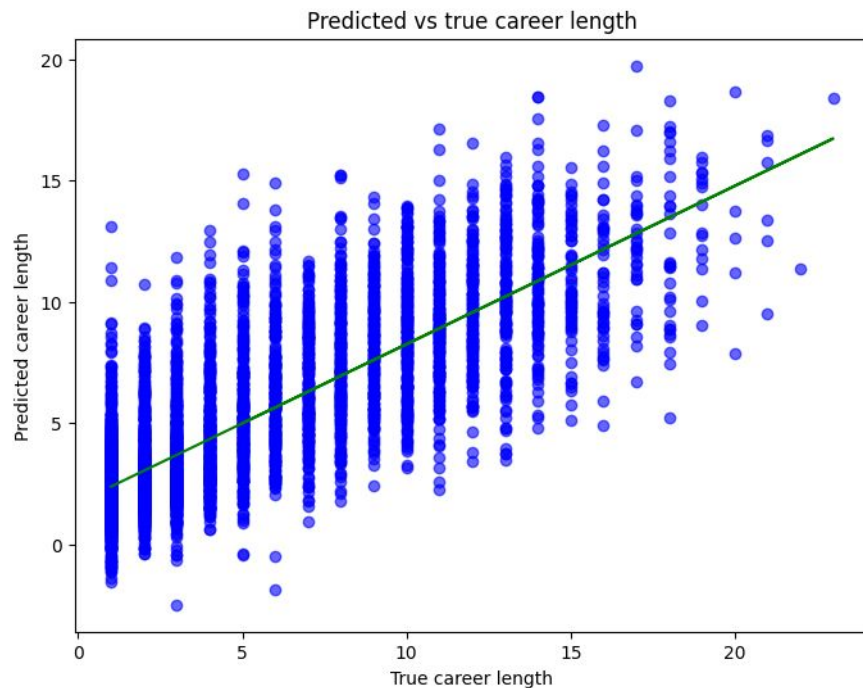
# Plotting with line of best fit

- The plot shows the **true retirement age** vs our **predicted retirement age** with a positive relationship!
- We included the line of best fit to show the positive relationship



# Plotting with line of best fit

- This plot shows the **true career length** vs our **predicted career length**, which also has a positive relationship!



# Results

- Use the **MSE loss function** to determine the accuracy of prediction.
- RMSE gives us the number of years we are expected to be off by in our predictions.
- For the **career length case**:
  - $RMSE=2.57$
  - $R^2 = 0.6699$
- For the **age predictor case**:
  - $RMSE=3.35$
  - $R^2=0.4772$

# Analysis

- Our model **more accurately predicts career length** over retirement age
- RMSE being 2.57 for career length means that **we are approximately 2.57 years off in predicting career length per prediction on average.**
- $R^2$  being 0.6699 means **our model explains 66.99% of the differences in career length.**
- Our plotting results show us that **the relationship between true and predicted values is positive!**

# Additional Plans

- Find more complete data for injuries
- Use injury information in a more complex way (severity of injury)
- Use data on player income
- Try different modeling methods and loss functions to reduce error
- Wait for currently active players to retire to see how accurate our predictions are



**Thank you!**