

The background of the slide is a dark blue basketball court. It features white lines for the three-point arc, free-throw line, key, and center circle. There are several small, semi-transparent squares scattered across the court, representing player positions. Some squares are red, some are orange, and one is teal. The title text is centered over the court.

NBA PLAYER CLASSIFICATION

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INTRODUCTION

GOAL:

Create a model that classifies NBA players beyond the traditional 5 positions (PG, SG, SF, PF, C)

Provide insight on team makeup of the top and bottom teams to see what good teams have that bad teams lack

PROBLEMS TO ADDRESS

Player A

0/0.2 3P per game

14.3 3P%

Position: Center



2015 Brook Lopez

Player B

1.8/5.2 3P per game

34.6 3P %

Position: Center



2016 Brook Lopez



PROBLEMS TO ADDRESS

Differences Within Positions

A player's position is not always a good indicator of that player's playstyle

Manually (or automatically) generate types of playstyles to classify players better

Player Development

Players are always evolving, which can result in different playstyles between seasons

Count each season of a player as a different player
Eg. 2015 Brook Lopez and 2016 Brook Lopez would be different players

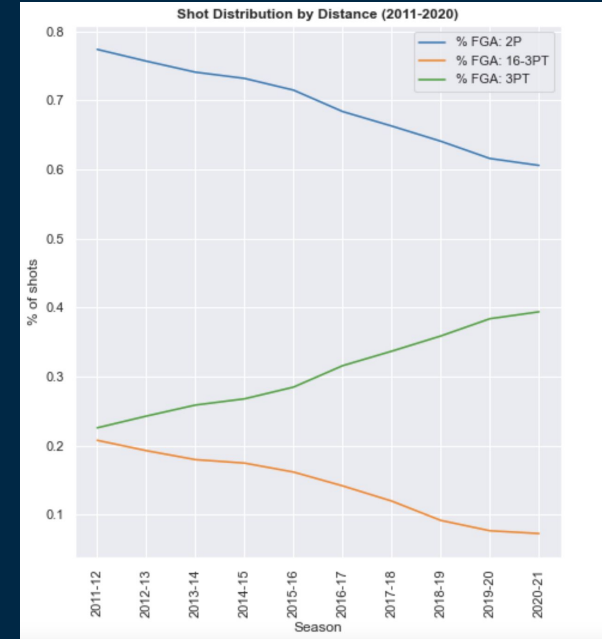
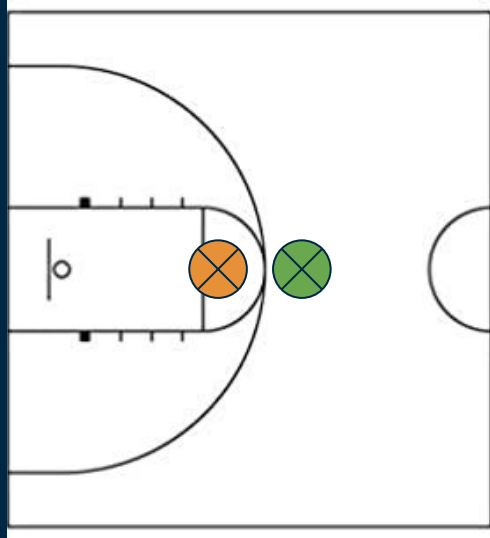


UNDERSTANDING THE PROBLEM

3 Point Era

Teams have started to trade the “long 2” (midrange) for the 3 pointer

2015
Stephen Curry's 1st MVP
Warriors best record in NBA
Led NBA in 3P% (.398)



3PT per game had been increasing but seeing the Warriors' success as a mainly 3PT shooting team in 2015 was what triggered a spike

This project only uses player data from 2015-2021

THE DATA

Gathered/Scraped from:

- NBA.com
- Basketball-reference

Contains:

- Traditional player stats (points, rebounds, FG %, etc.)
- Shot location/tendencies (midrange shooting, drives, postups, etc.)



MODELING: SEMI-SUPERVISED LEARNING

Unsupervised learning

Clustering algorithm separates players into groups, after which, give each group a playstyle

Supervised Learning

Classification model is trained using the groups from the unsupervised learning results as the labels



MODEL RESULTS

Best Model: Neural Network

Training Accuracy: 97.3%

Test Accuracy: 94.2%

Loss: 0.0926

Playstyles:

0. Ball-Dominant Scorer

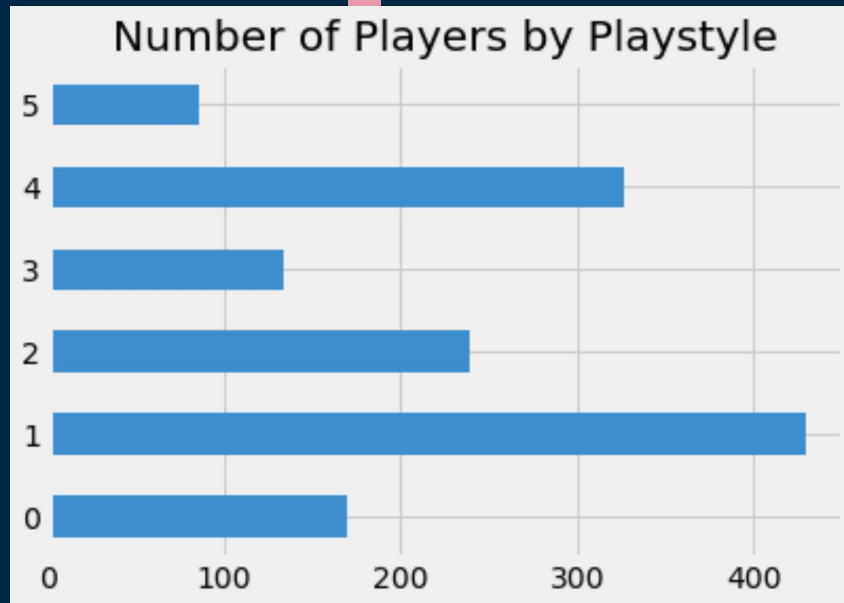
1. Role Player

2. Stretch Big

3. Traditional Big

4. Secondary Guard

5. High-Usage Big



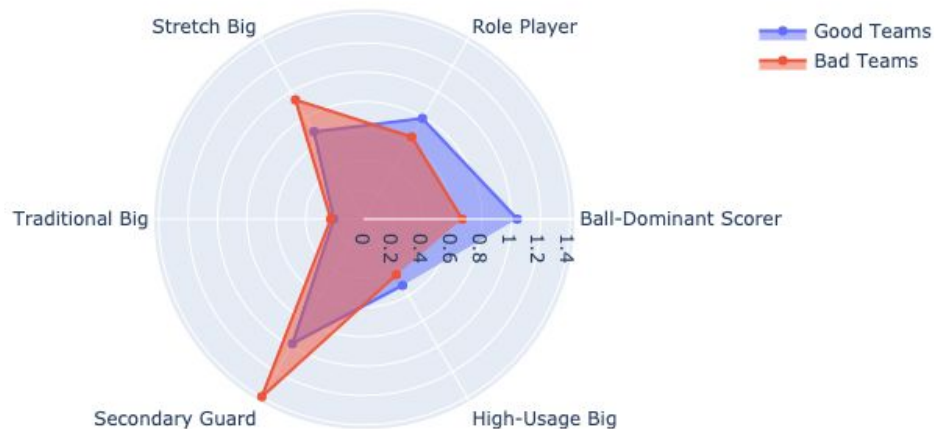
MODEL RESULTS: SEMI-SUPERVISED

Comments:

- Good teams have more
 - Ball-dominant scorers
 - Versatility in role players
- Bad teams have more
 - Stretch Bigs
 - Secondary Guards

Highlights importance of a Ball-Dominant Scorer and prioritizing a superstar on the roster over team depth. In today's NBA, it may be better to have a superstar surrounded by decent players, rather than a deep team of good players.

[0] NBA Team Composition: Semi-Supervised Model



FUTURE WORK

DASHBOARD: CLASSIFIER



Used to generate
predicted playstyle
based on
user-inputted stats

DASHBOARD: PLOTING



Create interactive
tool that allows
users access radar
plots by toggling
years and team-type
(good, bad, average)

DEFENSIVE CLASSIFICATION



Most of these
classifications mainly
concern offense. More
defensive stats could
show which positions
need the best defense.

Do you have any questions?

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THANK YOU!



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