



Analysis of the Mid-Range Jumper in the Big 12

Jacob Kauffman

Rice University



THE MID-RANGE JUMPER:



THE LEAST
EFFICIENT SHOT IN
BASKETBALL?

OR

A CONFERENCE
CHAMPIONSHIP
WINNER?



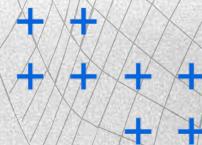
OVERVIEW

I. Data Cleaning Process

2. Data Visualization

3. Multi-variate Linear Regression

4. Machine Learning Predictions



DATA CLEANING



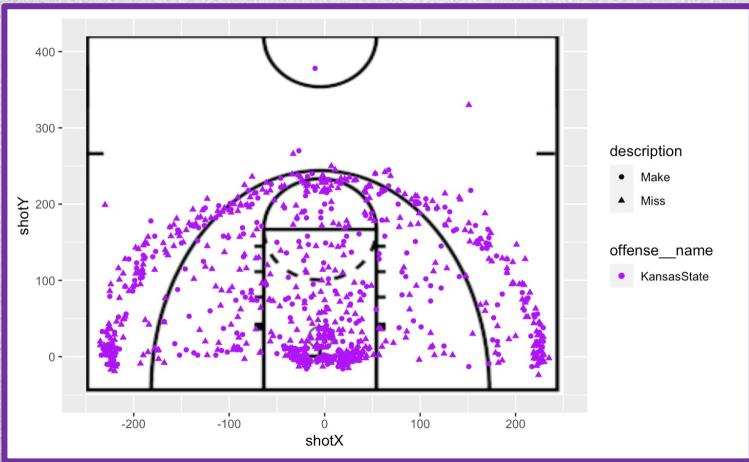
Current dataset:
19,000
possessions
90 Big-12 games

Want to filter to
only a few columns
of particular
interest

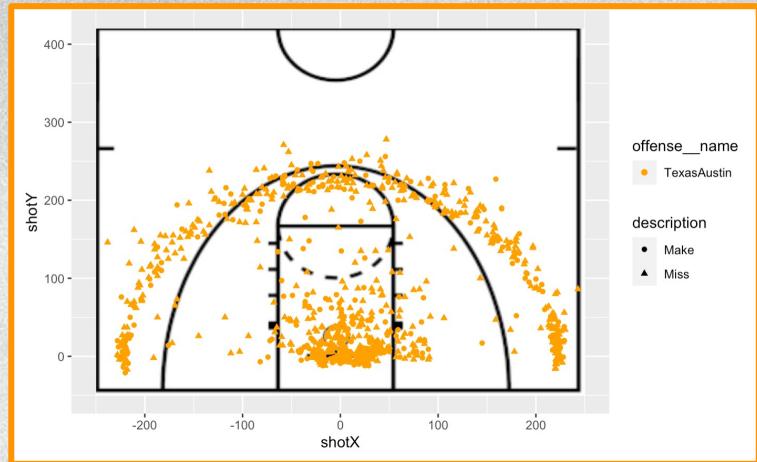
Ultimately want to
aggregate data to
season level



SHOT VISUALIZATION COMPARISON



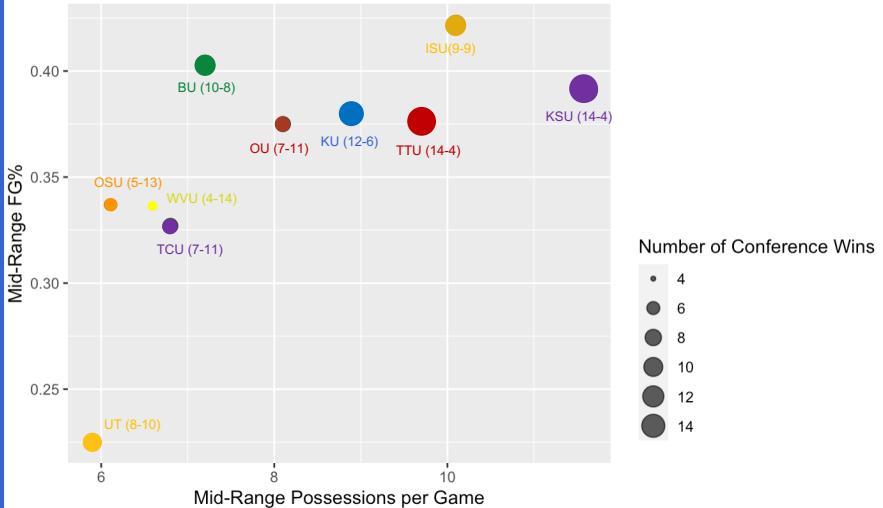
Kansas State (14-4)
Conference Champions



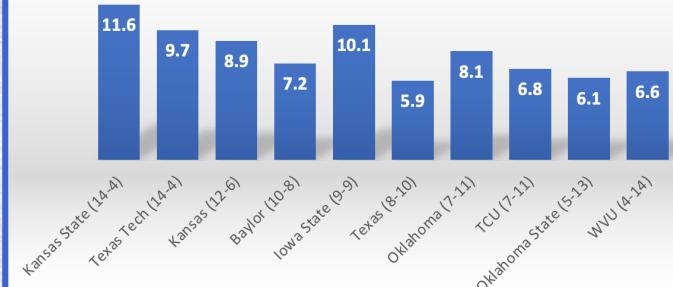
Texas (8-10)
Missed NCAA Tournament

++ WINNING TEAMS TAKE/MAKE MORE MID-RANGE SHOTS ++

Wins increase with more frequent/effective mid-range shooting



Midrange Possessions Per Game





MID-RANGE/FG% REGRESSION

Midrange and FG% Regression on Wins

Dependent variable: Wins	
Mid_rate	1.422*** (0.301)
Mid_FG	36.580* (14.809)
Three_FG	32.425 (60.147)
Rim_FG	16.180 (42.375)
Constant	-12.165 (17.321)
Observations	10
R2	0.895
Adjusted R2	0.811
Residual Std. Error	2.150 (df = 5)

Note: *p<0.1; **p<0.05; ***p<0.01

*data used for regression on slides 11 and 12 in appendix

1.

Interestingly, only two of the four regressors here are statistically significant:

2.

These are mid-range attempt rate, and mid-range FG%

3.

One point increase in Mid-Range FG% leads to more expected wins than the same increase in 3P FG% or Rim FG%



BAYLOR CASE STUDY

Specific Case Study:

Baylor:

2018-19 Conference Season:
**7.2 Midrange
Possessions/Game (6th/10)**

40.3% Midrange
FG% (2nd/10)

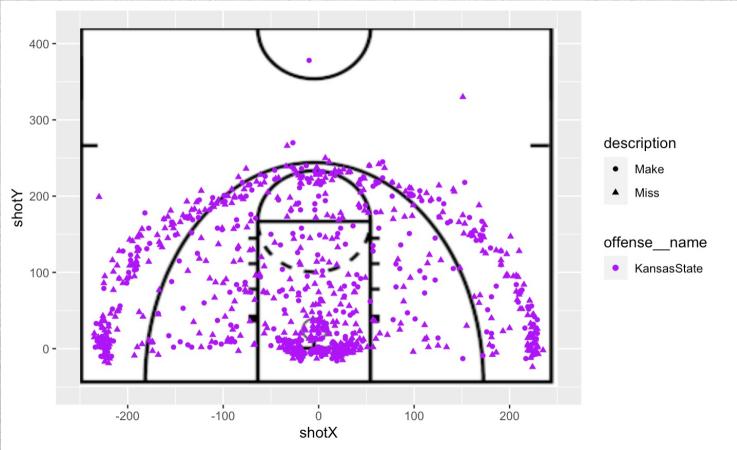


What happens if Baylor
increase Midrange
possessions by 75%?:

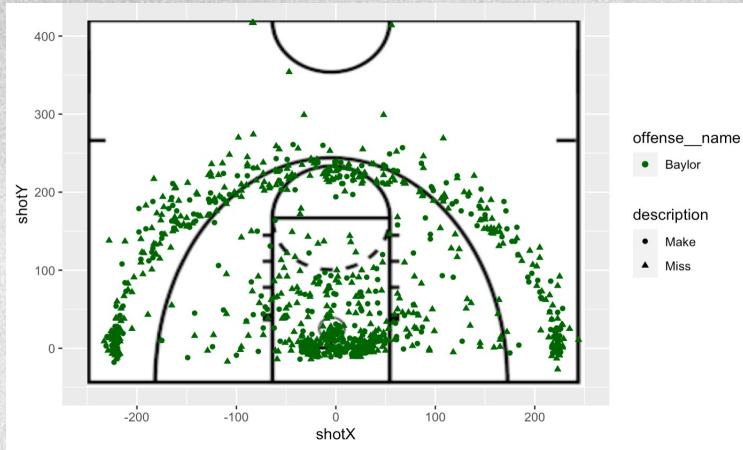
**12.6 Midrange
Possessions/Game (1st/10)**



SHOT VISUALIZATION COMPARISON



Kansas State (14-4)
Conference Champions



Baylor (10-8)
Lost both matchups to KSU

MACHINE LEARNING TO PREDICT BAYLOR'S SEASON

1. • Filter data to include only Baylor's possessions
2. • Duplicate Baylor's data and double every mid-range possession while eliminating the same number of random non-midrange possessions
3. • Split both datasets into training and test groups, and add a shot outcome column variable for the training group
4. • Employ a Random Forest ML Model that predicts shot outcomes for both test groups
5. • Employ a Monte Carlo Simulation that randomly samples Baylor's season from both train sets 10,000 times, averaging PPG and wins.

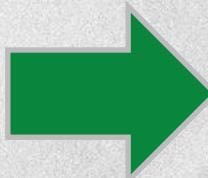
BAYLOR CASE STUDY: MACHINE LEARNING OUTCOME

Specific Case Study:

Baylor:

BEFORE:

- Expected Record of 10.3-7.7
- 72.6 expected PPG



AFTER:

- Expected Record of 11.4-6.6
- 75.1 expected PPG



PROJECT TAKEAWAYS



Clear correlation between a team's propensity for mid-range shots and their success in conference



A 1% jump in Mid-range FG% leads to more expected wins than a 1% jump in 3P FG% or Rim FG%



For Baylor, 5 more mid-range possessions per game leads to more than one additional expected win

APPENDIX

Team <i><chr></i>	Mid_rate <i><dbl></i>	Mid_FG <i><dbl></i>	Three_FG <i><dbl></i>	Rim_FG <i><dbl></i>	Wins <i><dbl></i>
Kansas State (14-4)	11.6	0.391	0.3344595	0.568	14
Texas Tech (14-4)	9.7	0.377	0.3618182	0.639	14
Kansas (12-6)	8.9	0.380	0.3421517	0.612	12
Baylor (10-8)	7.2	0.403	0.3455344	0.585	10
Iowa State (9-9)	10.1	0.422	0.3601236	0.632	9
Texas (8-10)	5.9	0.225	0.3356941	0.580	8
Oklahoma (7-11)	8.1	0.375	0.3436364	0.591	7
TCU (7-11)	6.8	0.327	0.3555195	0.616	7
Oklahoma State (5-13)	6.1	0.337	0.3725191	0.591	5
WVU (4-14)	6.6	0.336	0.3123994	0.563	4

Data used for regression in slide 7: Midrange attempt frequency, Midrange FG%,
3P FG%, Rim FG%

