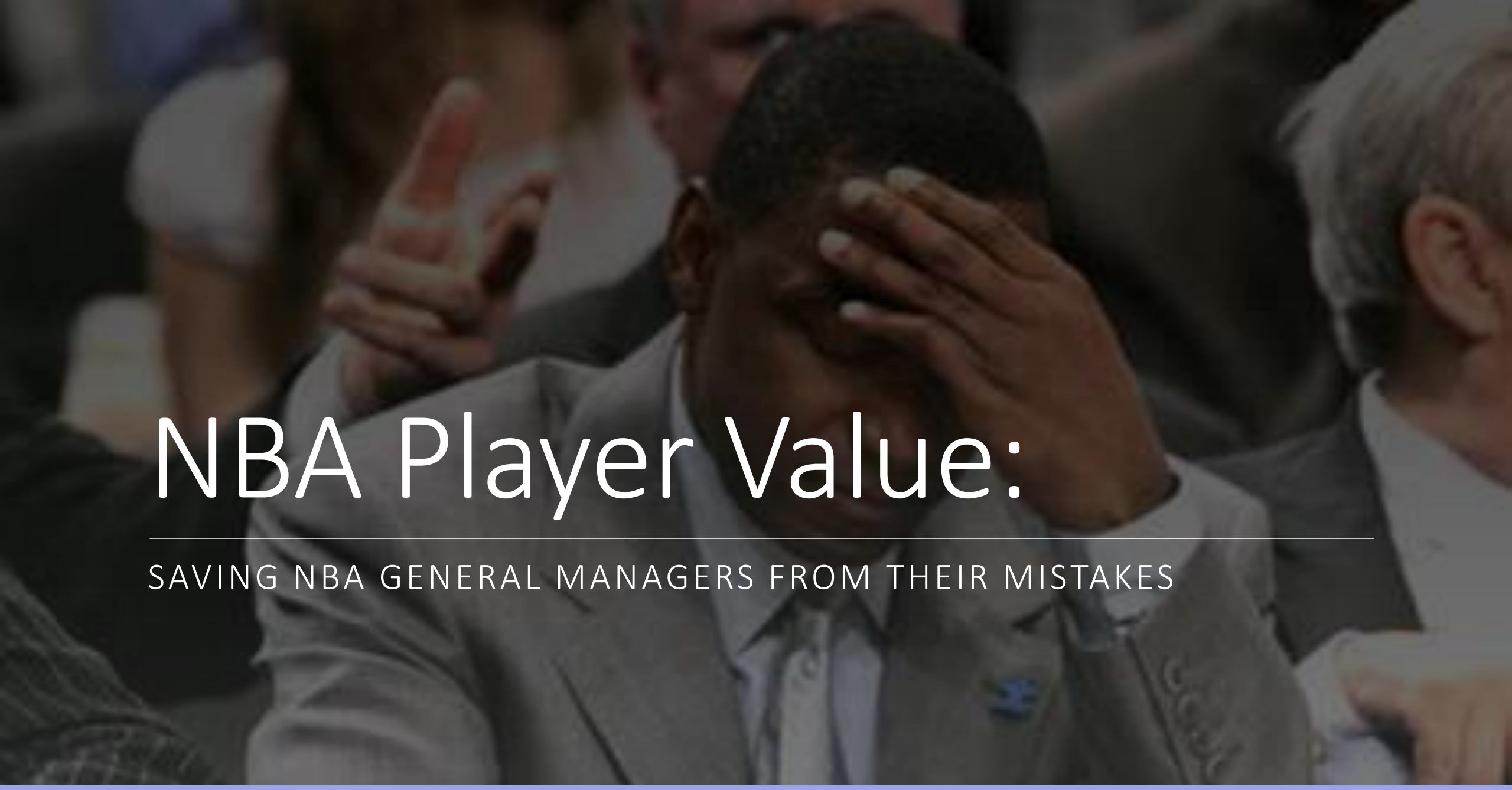


NBA Player Value:

SAVING NBA GENERAL MANAGERS FROM THEIR MISTAKES

The Problem

General Managers are tasked with the responsibility of constructing and paying a roster composed of high-level athletes—every one of which feels he ought to be paid what he is worth.

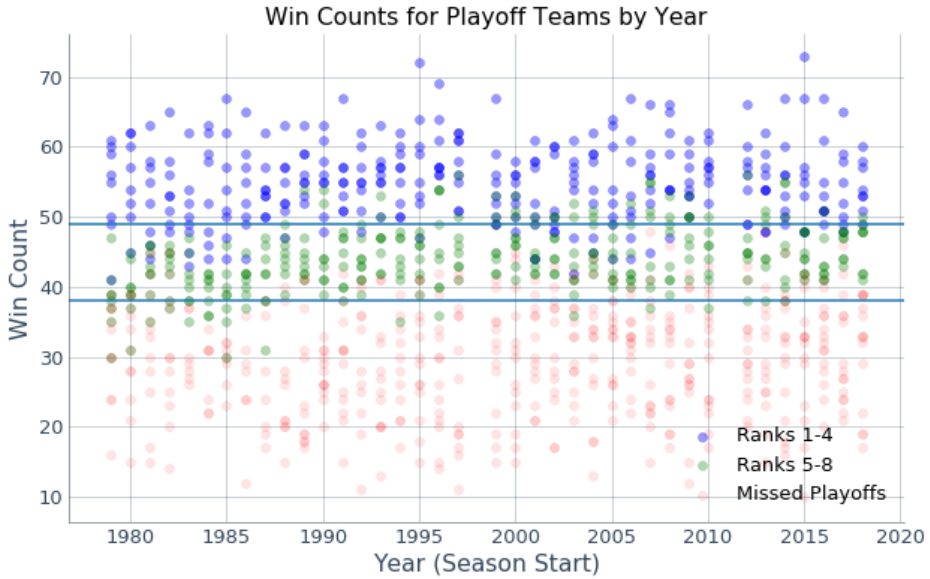
All too often, these GMs succumb to external pressures: to sign the player the fans want or that the media has placed on a pedestal, to pay a player more than he is worth out of fear of missing out on a player, offering too little to a player out of pride or fear (or both) and missing out—the reasons go on and on.

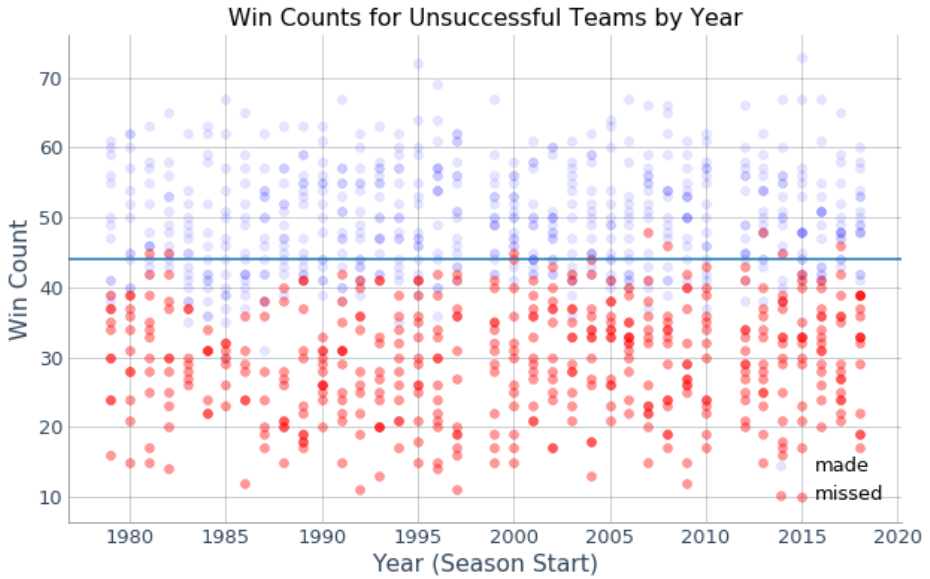
None of these pressures is based in anything objective. GMs need something on which to fall to make such costly and high stakes decisions, a means of defending the decisions they make.

As we saw in Michael Lewis' "Moneyball," professional sports leagues can be ruled by forces other than logic, but the game always has potential to be affected by it.

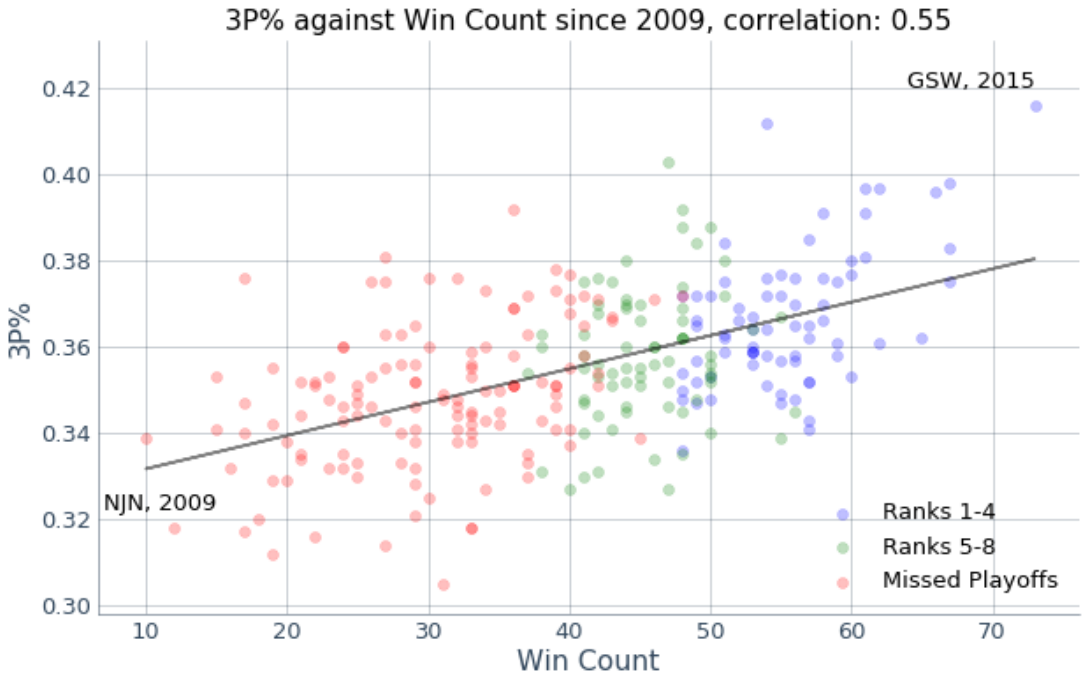
Using machine learning, we will look to give any GM an upper hand who is willing to take it.

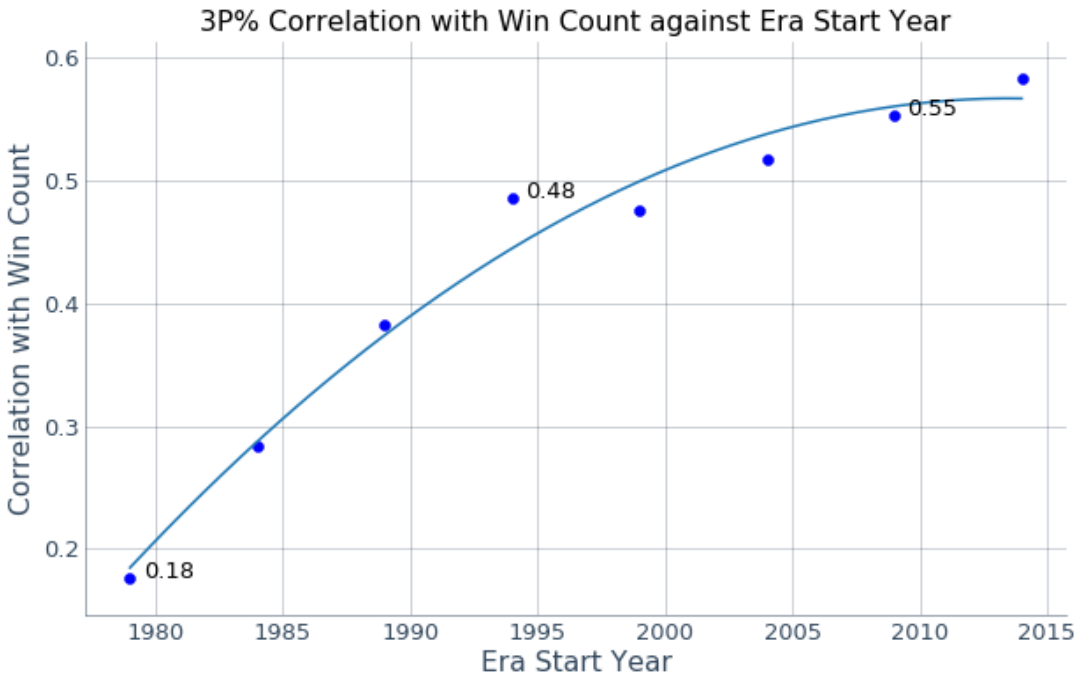
Step One: Identify Successful Teams


Win Counts for Playoff Teams by Year
Win Count
Year (Season Start)
Ranks 1-4
Ranks 5-8
Missed Playoffs


Win Counts for Unsuccessful Teams by Year
Win Count
Year (Season Start)
made
missed

Determine What Makes Teams Successful


3P% against Win Count since 2009, correlation: 0.55
GSW, 2015
NJN, 2009
Ranks 1-4
Ranks 5-8
Missed Playoffs
3P%
Win Count
0.42
0.40
0.38
0.36
0.34
0.32
0.30
10
20
30
40
50
60
70


3P% Correlation with Win Count against Era Start Year
Correlation with Win Count
Era Start Year
0.18
0.48
0.55
0.6
0.5
0.4
0.3
0.2
1980
1985
1990
1995
2000
2005
2010
2015

Step Two: Determine Player Value

Using updated player positions from a linear discriminant analysis, along with key career and year-to-year statistics, develop models that will give the best possible and most objective dollar amount to any specific player

Step Three: Make Recommendations

Using Machine Learning, predict player salary given such features as position, age, and relevant playing statistics

Make recommendations for teams looking to make cuts, sign new players, or restructure contracts

Turn recommendation system into accessible web application

THE VALUE OF GETTING IT RIGHT

DIRECT VALUE:

A bad player contract can cripple a team for upwards of a dozen years. For example, someone owed $25 million but provides $1 million worth of value to the team effectively gives their team $24 million less to work with than the average teams elsewhere in the league.

INDIRECT VALUE:

When the salary cap is handled such that the majority of players on a team are paid only what they are worth and no more, a team can allow for a high-level player or player to be signed for more than they might be worth—a “max-level” player whose impact extends past statistics by increasing ticket sales because of his style of off-court personality.

The Data

The data will be scraped from the stats website “basketball-reference.com” and will include team and individual player data dating back to 1979.

Salary data will be scraped from “hoopshype.com” but is only available as far back as the 2000-2001 season and will thereby limit the scope of our full analysis.

Deliverables

Deliverables after completion of this project will include:

1. Source code, shared in GitHub repo across multiple juypter notebooks
2. A slide deck, detailing what was accomplished and to what degree
3. A blog post or paper, that will go much more in depth concerning the “how”
4. Hopefully, a web application, potentially written in Java, that will allow readers to recreate the important final step of the project’s objectives and find a valuable yet affordable player for their own NBA franchise, a player they’d otherwise most certainly miss.