HE Consulting Co.
Heytea
Everyday

Lakers Savers

MGT 4187 2022 Fall, Final Project Presentation, by Heytea Everyday

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Who are we ?

Heytea
Everyday

Professional lineups advice
for NBA teams based on

Team’s Weakness

Player’s Ability

Salary Constraints

Content

- Background Overview
- Methodology
- Data Inspection & Exploration
- Model Construction & Results
- Limitations
- Conclusion

PART 01

Background Overview

National Basketball Association (NBA) Overview

National Basketball Association

The ***National Basketball Association (NBA)*** is **the world's premier men's professional** basketball league and one of the major professional sports leagues of North America.

There are **30 teams** which are divided into western and eastern conferences and **500 - 600 players** joining the different 30 teams.

Lakers is a famous NBA team. It joined in NBA **in1948**. At that time the team were called Minneapolis Lakers.But now they changed there name to Los Angeles Lakers because of the aircraft UNL in 1960.

Los Angeles Lakers

Background Overview

Problem & Aim

16 *NBA Final Champions*

1949, 1950, 1952, 1953, 1954, 1972, 1980, 1982, 1985, 1987, 1988, 2000, 2001, 2002, 2009, 2020.

Today's *Lakers*

LOS ANGELES LAKERS

6 – 11 | 13th in Western

***Winning Rate:* 35%**

How to ***find the most suitable lineups*** for Lakers to improve their performance?

PART 02

Methodology

- Machine Learning
- Data Mining
- Classification
- Decision Tree
- Stochastic simulation

How the analysis conduct: Overview

How to save Lakers?

Step 01

Player Scoring Model based on past data

$Overallrating = \alpha bio + \beta ftm + \gamma 3pm + \ldots + error$

Step 02

Predict player's overall performance
in **Season 2022-23 (up to now)** based on the model

Step 03

Analyze *the Lakers'* **current player lineup problems**

Step 04

Classify players & **Recommend** new player lineups

Step 05

Validate the effectiveness of the new lineup

How the analysis conduct: Methodology

Methodology	Overview	Analogy

How to save Lakers?

Step 01

Player Scoring Model based on past data

$Overallrating = \alpha bio + \beta ftm + \gamma 3pm + \ldots + error$

Step 02

Predict player's performance
in **Season 2022-23 (up to now)** based on the model

→ **Machine Learning** (Steps 01–02)

Step 03

Analyze *the Lakers'* **current player lineup problems**

→ **Data Mining**

Step 04

Classify players & **Recommend** new player lineups

→ **Classification & Decision Tree**

Step 05

Validate the effectiveness of the new lineup

→ **Stochastic Simulation**

How the analysis conduct: Methodology

Methodology	***Overview***	***Analogy***
	How to save Lakers?	***"Market Shopping"***
Machine Learning	**Step 01** **Player Scoring Model** based on past data $Overall rating = \alpha bio + \beta ftm + \gamma 3pm + \ldots + error$	**Merchandise Pricing**
Machine Learning	**Step 02** **Predict player's performance** in **Season 2022-23 (up to now)** based on the model	**Merchandise Pricing**
Data Mining	**Step 03** **Analyze** *the Lakers'* **current player lineup problems**	**Analysis of Customer needs**
Classification & Decision Tree	**Step 04** **Classify** players & **Recommend** new player lineups	**Recommend products to customers**
Stochastic Simulation	**Step 05** **Validate the effectiveness** of the new lineup	

PART 03

Data Inspection & Evaluation

- Data source & validity

Data Sources & Validity: All data from official webs

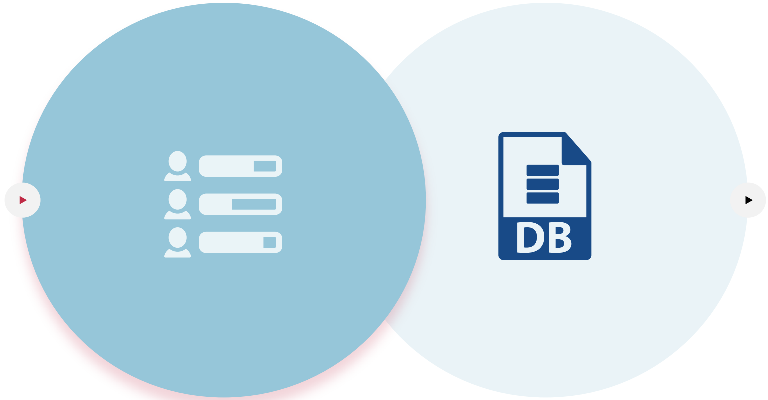
- **From NBA official websites**
- **Cover 2 regular seasons: 2021-2022, 2022-2023 (up to now)**
- ***BIO data + On-field Performance***

Two
Main Datasets

- **From NBA 2K (game launched by official)**
- **Reflects overall performance in 2022**

Past NBA Players Overall Ratings

Target Variable y



Past NBA Players Stats

Independent Variables Xi

$$\hat{y}_i = \frac{1}{B}\sum_{b=1}^{B}\sum_{m=1}^{M}\hat{\alpha}_m^b \mathbf{1}(X_i^b \in R_{m,b}^L)$$

PART 04

Model Construction & Results

Model I : Machine Learning - Prediction of Player's Ability

Model Constructions

Player's stats in 2021-22

PLAYERS	GP	MIN	PTS	FGM	…
Stephen Curry	64	34.5	25.5	8.4	…
Russell Westbrook	78	34.3	18.5	7.0	…
LeBron James	56	37.2	30.3	11.4	…
…	…	…	…	…	…

Estimated Label

Player's stats in 2022-23

PLAYERS	GP	MIN	PTS	FGM	…
Stephen Curry	18	34.6	31.7	10.9	…
Luka Doncic	16	37.1	34.0	11.6	…
Kyrie Irving	12	36.0	25.1	9.3	…
…	…	…	…	…	…

Model I : Machine Learning - Prediction of Player's Ability

Regression Performance

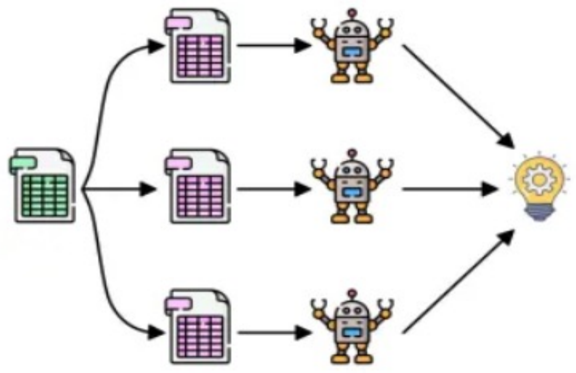
Regression Method	Training Points	Testing Points
Liner	0.846244	0.694946
Ridge	0.817059	0.759697
Bagging	0.937380	0.749120
KNN	0.810436	0.699067
SVR	0.731888	0.581524
Lasso	0.004152	-0.003536
MLP	0.862328	0.686144
DecisionTree	1.0	0.384726
ExtraTree	1.0	0.340967
AdaBoost	0.860429	0.792255

Bagging Regression

$$\hat{y}_i = \frac{1}{B}\sum_{b=1}^{B}\sum_{m=1}^{M}\hat{\alpha}_m^b \mathbf{1}(X_i^b \in R_{m,b}^L)$$

X_i^b **means the data point of the b^th^ bootstrap**

Bagging



Parallel

Model I : Machine Learning - Prediction of Player's Ability

TOP 20 estimated players

Rank	Players	Points
1	Luka Doncic	92.3
2	Joel Embiid	91.9
3	Giannis Antetokounmpo	91.8
4	Donovan Mitchell	91.3
5	Stephen Curry	91.3
6	Damian Lillard	90.7
7	Pascal Siakam	90.2
8	Jayson Tatum	90.1
9	James Harden	90
10	Shai Gilgeous-Alexander	90
11	Nikola Jokic	89.8
12	Trae Young	89.2
13	Ja Morant	89.2
14	Anthony Davis	89
15	Kyrie Irving	89
16	Kevin Durant	88.9
17	Darius Garland	88.7
18	Paul George	88.7
19	Devin Booker	88.6
20	De'Aaron Fox	88.2

Nov 25th Kia MVP Ladder

Rank	Players
1	Luka Doncic
2	Jayson Tatum
3	Nikola Jokic
4	Giannis Antetokounmpo
5	Stephen Curry
6	Donovan Mitchell
7	Devin Booker
8	Anthony Davis
9	De'Aaron Fox
10	Ja Morant

Nov 18th Kia MVP Ladder

Rank	Players
1	Luka Doncic
2	Jayson Tatum
3	Giannis Antetokounmpo
4	Nikola Jokic
5	Ja Morant
6	Joel Embiid
7	Shai Gilgeous-Alexander
8	Devin Booker
9	Donovan Mitchell
10	Stephen Curry

Nov 11st Kia MVP Ladder

Rank	Players
1	Giannis Antetokounmpo
2	Luka Doncic
3	Jayson Tatum
4	Donovan Mitchell
5	Ja Morant
6	Devin Booker
7	Nikola Jokic
8	Kevin Durant
9	Damian Lillard
10	Stephen Curry

Nov 7th Kia MVP Ladder

Rank	Players
1	Giannis Antetokounmpo
2	Luka Doncic
3	Donovan Mitchell
4	Ja Morant
5	Devin Booker
6	Damian Lillard
7	Jayson Tatum
8	Pascal Siakam
9	Nikola Jokic
10	Shai Gilgeous-Alexander

Model II : Data Mining - Shooting Conclusion

Shooting Dashboard (Rank Range 1-30)

RANK	PTS	FGM	FGA	FG%	3PM	3PA	3P%	EFG
2022-2023	**29**	**29**	23	**30**	**29**	22	**30**	**30**
2021-2022	22	21	20	21	22	20	21	23
Rank Change	**-7**	**-8**	**-3**	**-11**	**17**	**-2**	**-9**	**-7**

Model II : Data Mining - Shooting Conclusion

Shooting Dashboard (Rank Range 1-30)

#	Implication
1	Restricted Area
2	In the Paint (Non-Ra)
3	Mid-Range
4	Left Corner 3
5	Right Corner 3
6	Corner 3
7	Above the Break 3

Season 2022-2023: FGM

#	1	2	3	4	5	6	7
RANK	1	23	23	27	21	24	21

Season 2022-2023: FGA

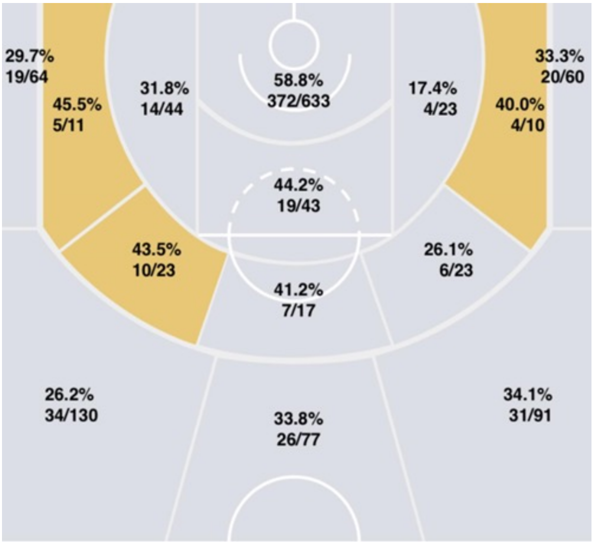
#	1	2	3	4	5	6	7
RANK	1	16	1	16	12	10	**28**

Season 2022-2023: FG%

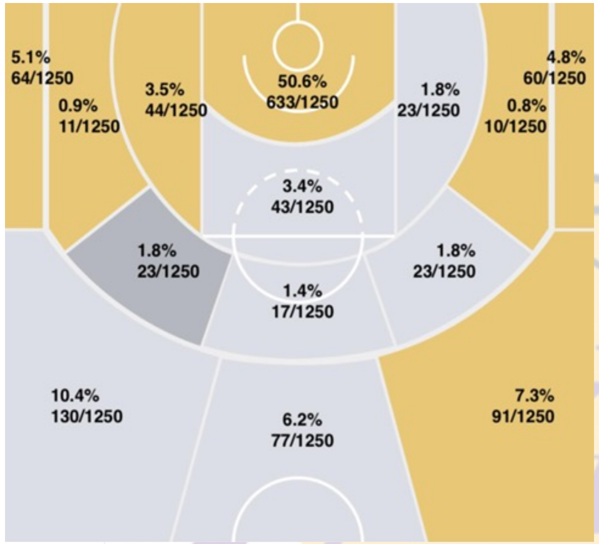
#	1	2	3	4	5	6	7
RANK	10	**26**	**28**	**28**	23	**30**	**27**

Model II : Data Mining - Shooting Conclusion

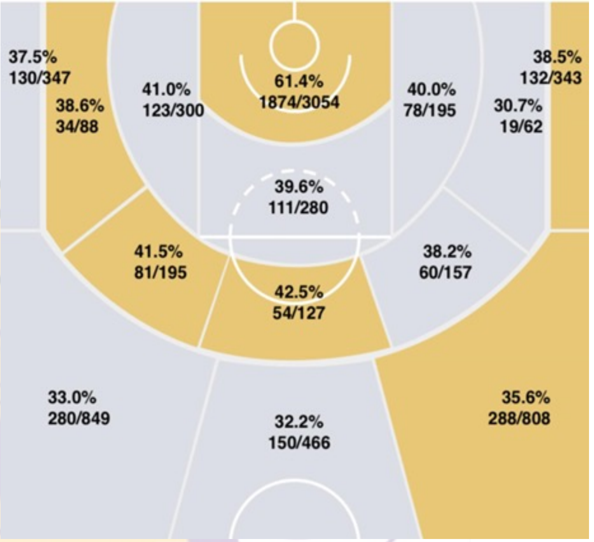
2022-2023
Shooting rate in each area



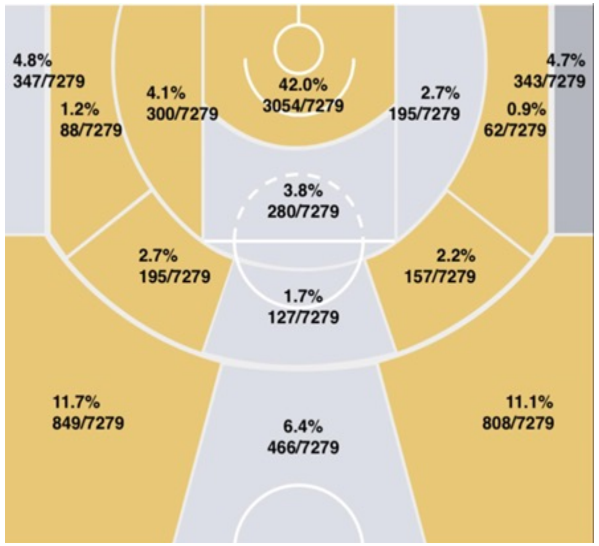
2022-2023
Distribution of shots by area



2021-2022
Shooting rate in each area



2021-2022
Distribution of shots by area



- Above the league average
- On par with the league average
- Below the league average

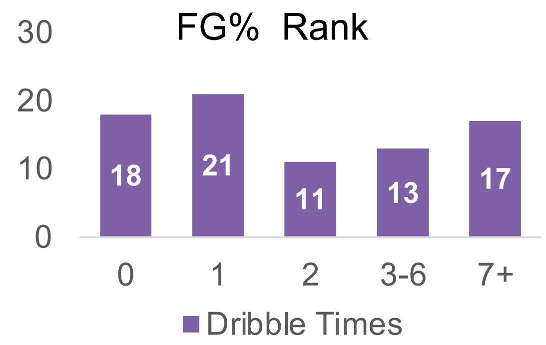
Conclusion

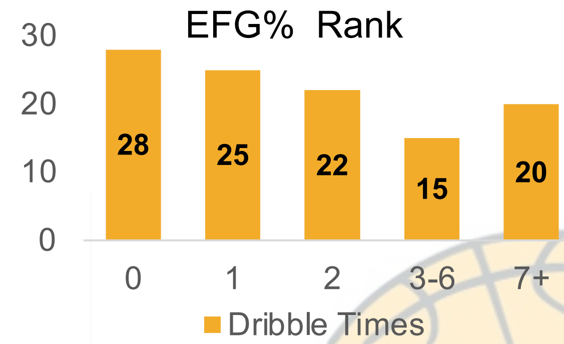
- **Abysmal overall shooting percentage**
- **Abysmal performance in other areas**
  (except for the offensive performance in the restricted area)

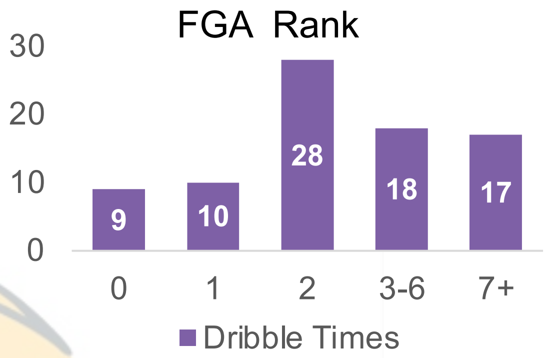
Solution

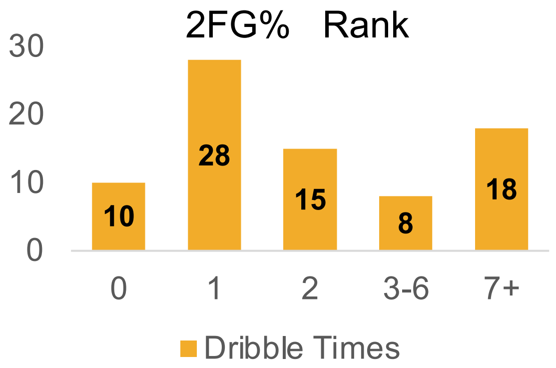
Shooters for every position (except restricted area).

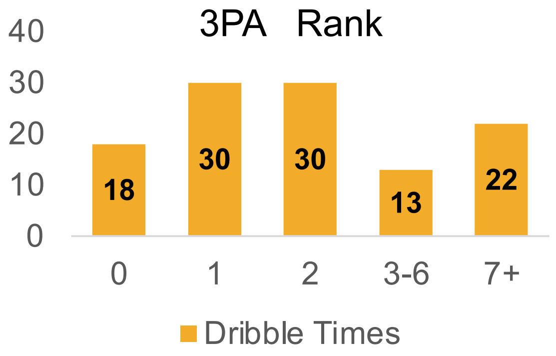
Model II : Data Mining - Dribble Analysis

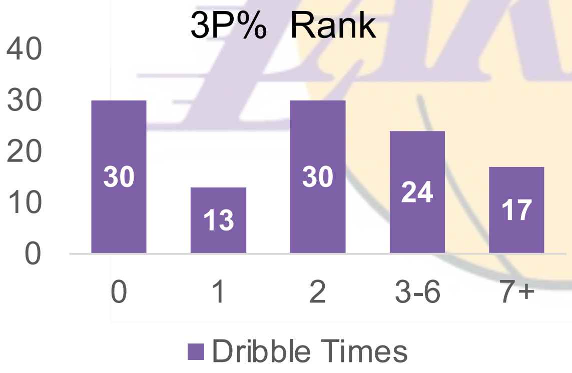


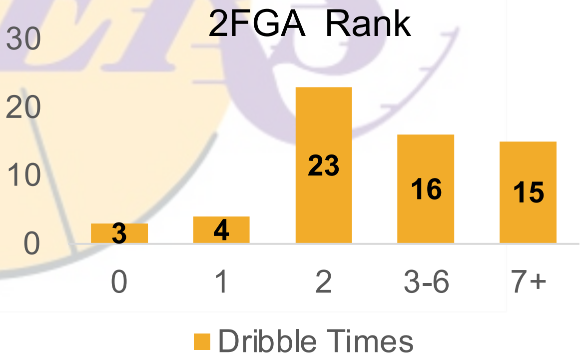












Conclusion

Low Zero & One Dribble shooting number and score rate

Solution

Good percentage in shooting quickly after the catch

Model II : Data Mining - Tracking Pass

Tracking Pass Dashboard

RANK	PASSES MADE	PASSES RECEIVED	AST	SECONDARY AST	POTENTIAL AST	AST PTS CREATED	AST ADJ	AST TO PASS%	AST TO PASS% ADJ
2022-2023	**28**	**28**	18	24	10	19	17	6	4
2021-2022	17	17	17	23	14	20	19	17	17
Rank Change	-11	-11	-1	-1	4	1	2	**11**	**13**

Conclusion

- **Cons:** Low number of passed and received times of the ball
- **Pros:** Relatively well done AST TO PASS%

Solution

- Enrich the tactical system
- Let the ball run
- Strengthen shooting ability after receiving the ball

Model II : Data Mining - Defense Conclusion

RANK	DEF RTG	DREB	DREB%	STL	BLK	OPP PTS OFF TOV	OPP PTS 2ND CHANCE	OPP PTS FB	OPP PTS PAINT
2022-2023	23	3	8	18	19	16	12	4	11
2021-2022	10	12	21	12	7	8	12	3	3
Rank Change	-13	9	13	-6	-12	-8	0	-1	-8

RANK	FREQ%	DFGM	DFGA	DFG%	FG%	DIFF%
2022-2023	21	25	15	27	1	30
2021-2022	16	13	12	17	16	15
Rank Change	**-5**	**-12**	**-3**	**-10**	**15**	**-15**

Non-Play-Off Level

Play-Off Level

Conclusion

- Most of the team's defensive stats are playoff-level
- Declined frequency of players jumping out to defend

Solution

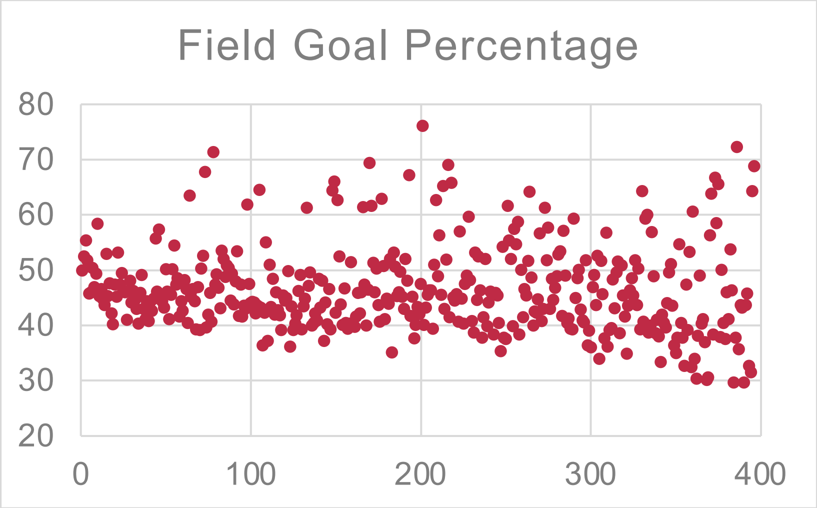
- Enhancing players with height and shot-blocking ability.
- Improve their defensive enthusiasm and effectively adjust their front line.

Model III : Classification - Player Ability Indicators

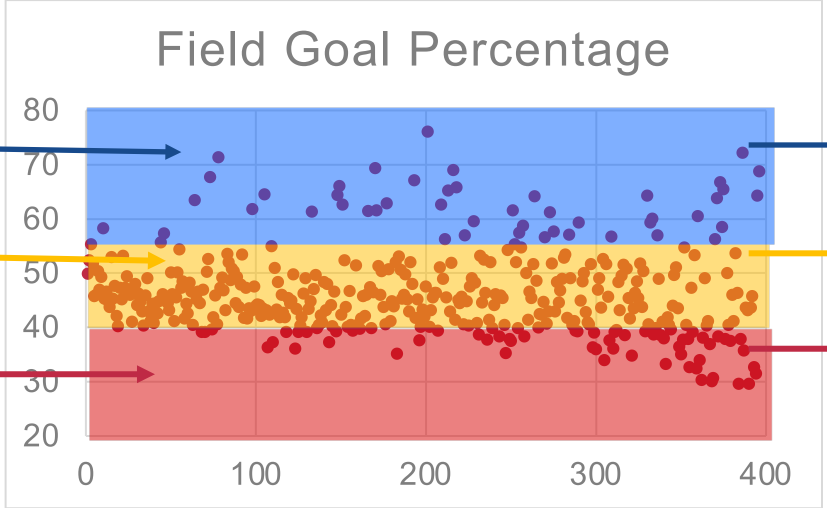
1 - dimension Index: (FG%)

FG% for all the 395 players

FG% Range: (28%, 76%)



Classification



High FG% → Accurate

Middle FG% → Normal

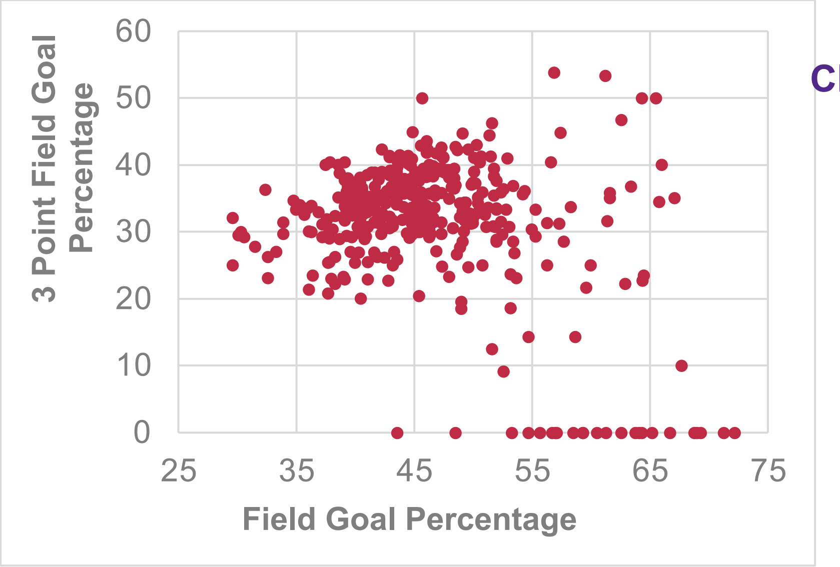
Low FG% → Inaccurate

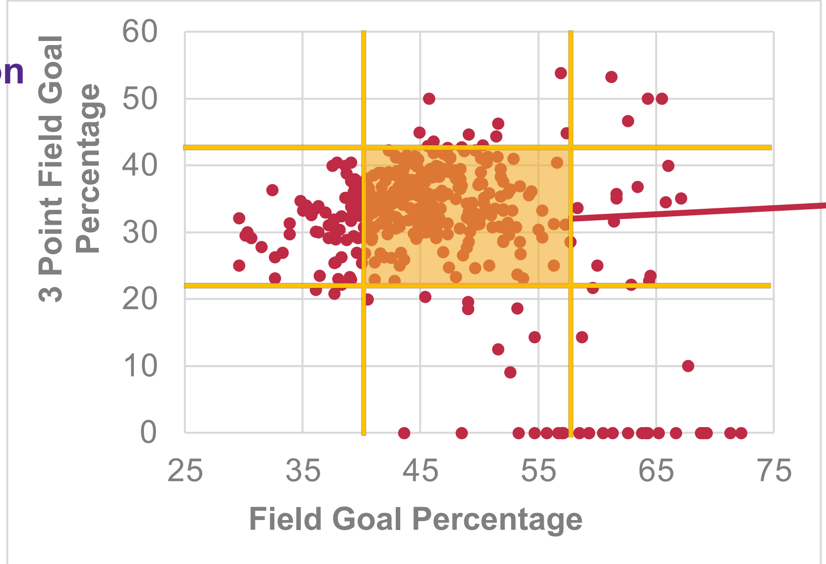
Label for classification

2 - Dimension Index: (FG%, 3P%)

FG% Range: (28%, 76%)

3P% Range: (0%, 54%)

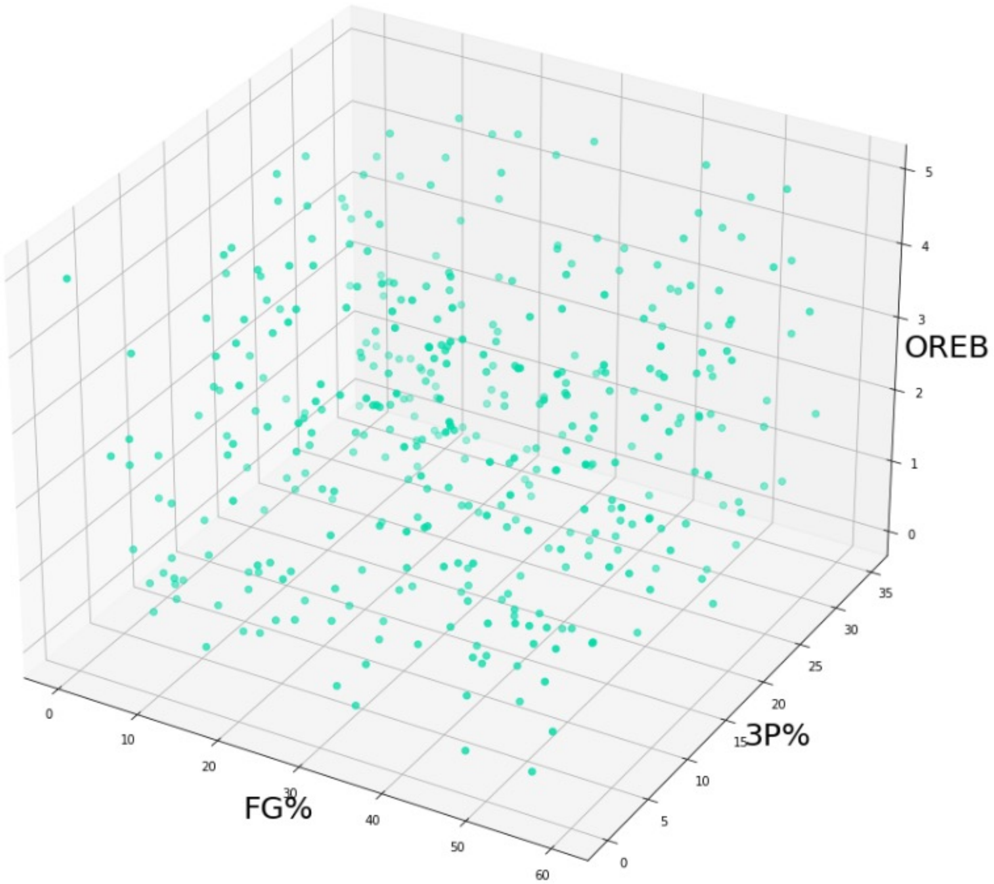


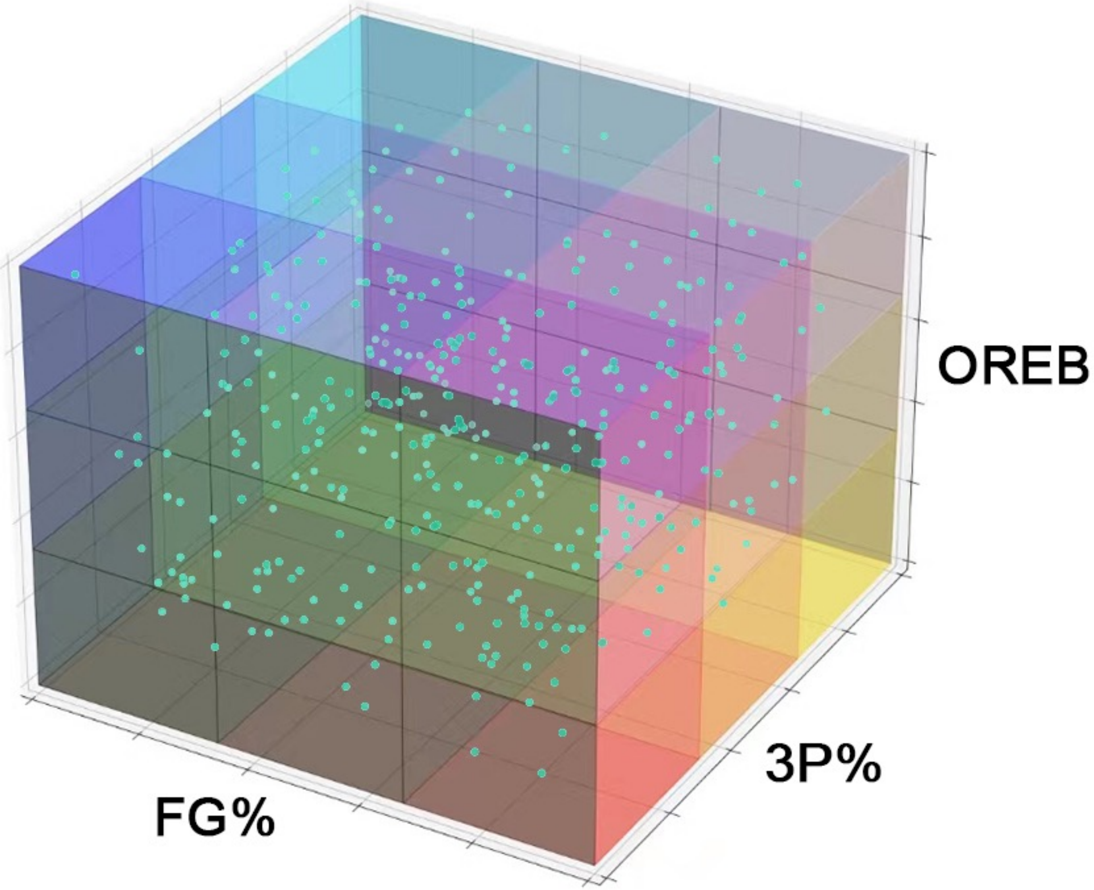


Stable three points shooters

Model III : Classification - Player Ability Indicators

3 - Dimension Index:
(FG%, 3P%, OREB)





Model III : Classification - Player Ability Indicators

N - Dimension Index: (PTS, FG%, 3P%, AST, REB......)

If every indicator's K = 3 ⇒ Possible Lables: 3^N

Best class is class_10;
Worst class is class_1

PTS : 30.6 points

AST : 6.2 assits

REB : 8.2 rebounds

FG% : 52.4%

TOV* : 3.5 turnovers

......

Classification by uniform ranking (K = 10)

PTS_rank : class_10

AST : class_10

REB : class_10

FG% : class_9

TOV* : class_1

......

Rank list of player ability indicators

Index	Class
PTS	10
AST	10
REB	10
FG%	9
TOV	1
......	......
PF	7

Number of Index: > 60

Model III : Decision Tree —— Player Arbitrage Model

14 Players in 2021-2022 season

Ranking Search Function

1. The indicators we focus on
2. The number of players we will trade
   Our decision: (Indicators, Number)

Target Traded Players

Ex:
(Indicators, Number) = ([PTS, FG%, 3P%], 2)

Indicators / *Players*	*Team ranking：PTS*	*Team ranking：FG%*	*Team ranking：3P%*
LeBron James	1	3	2
Horton Tucker	6	11	9
Avery Bradley	10	10	12
Kent Bazemore	14	14	14

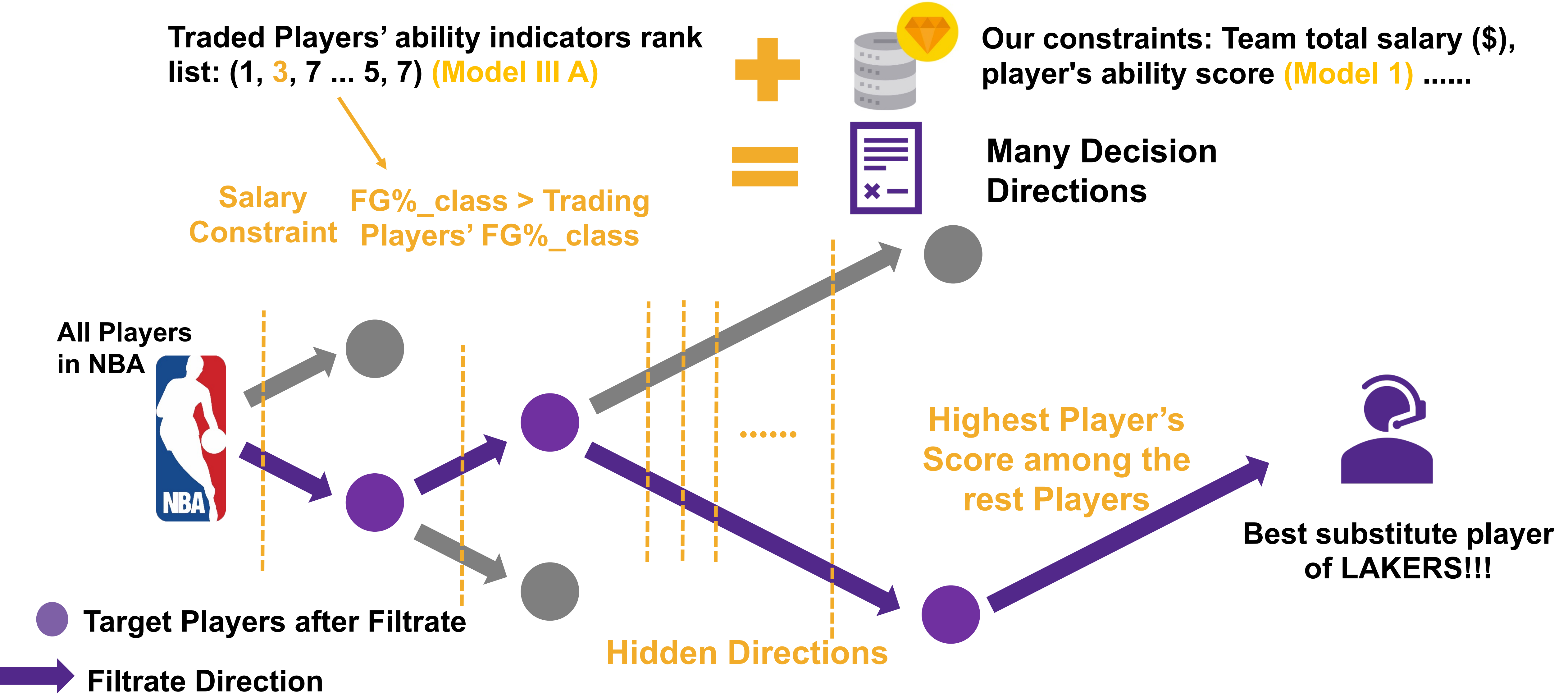
Traded Players

Poor performance

Normal Performance

Good performance

Model III : Decision Tree —— Player Arbitrage Model



Model III Outout: Help LAKERS

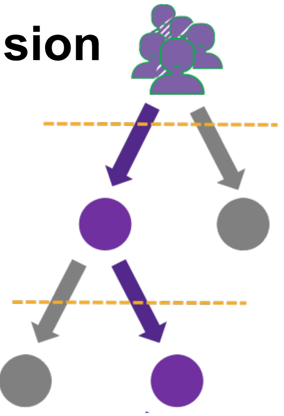
14 Players in
2021-2022 season

(Indicators, Number) =
([OREB, FG%, 3P%], 3)
(We want to strengthen the Lakers' offense from Data Mining)

Ranking Search Function

Traded Players:
(Talen Horton-Tucker, Kent Bazemore, Trevor Ariza)

Decision Tree



Best substitute players:
(Jakob Poeltl, Desmond Bane, Isaiah Roby)

MAKE LAKERS GREAT AGAIN!

Model IV : Open-source stochastic simulation machine for testing.

Original Lineup:

Verification idea: Run a t-test based on results of the Stochastic simulator to verify whether our adjusted rotation can improve the winning rate.

Model IV : Open-source stochastic simulation machine for testing.

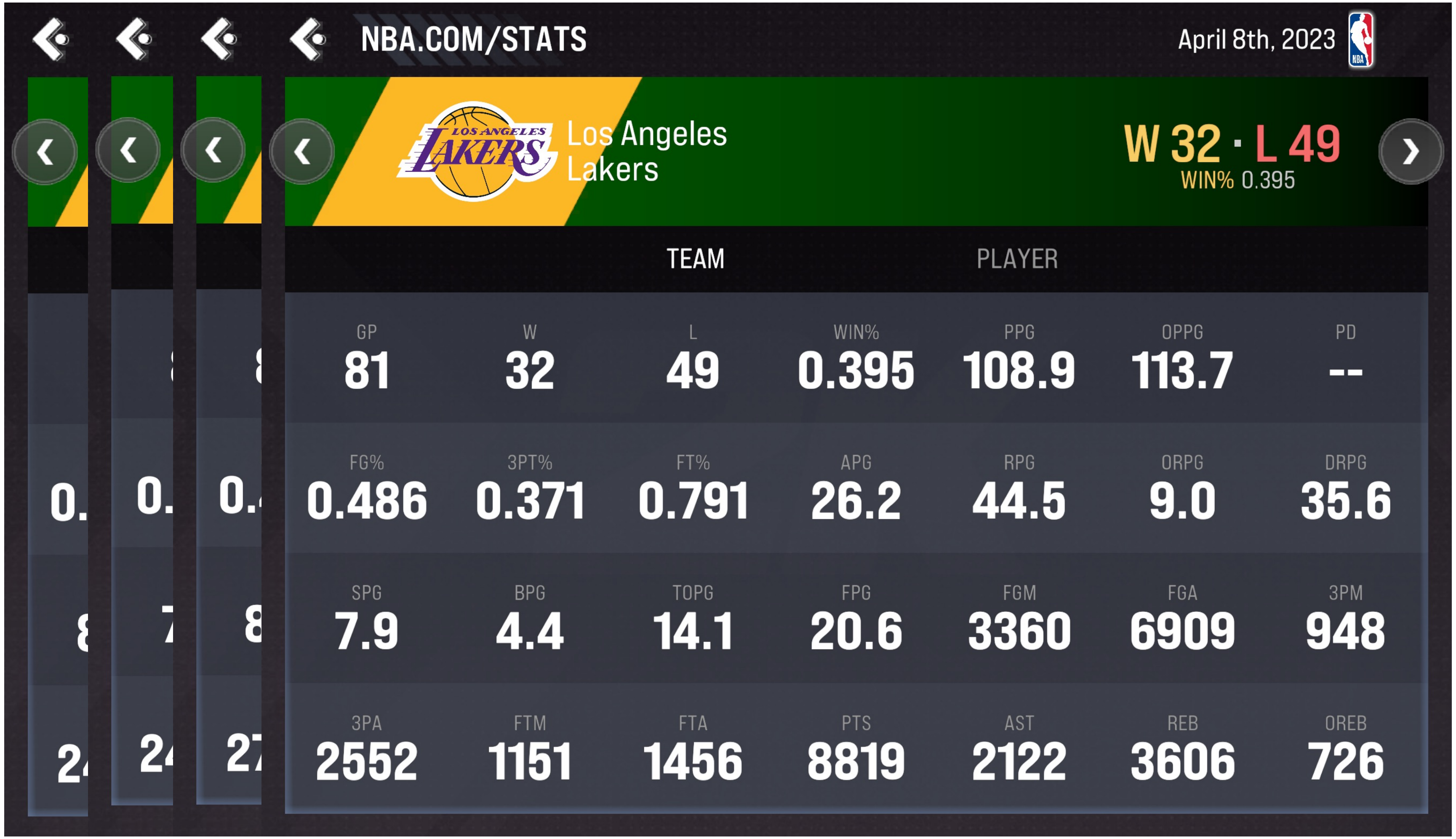
Changed Lineup:

Verification idea: Run a t-test based on results of the Stochastic simulator to verify whether our adjusted rotation can improve the winning rate.

Model IV : Open-source stochastic simulation machine for testing.

If we **do not** change the lineup of Lakers: average winning rate for Lakers is **42.42%.**

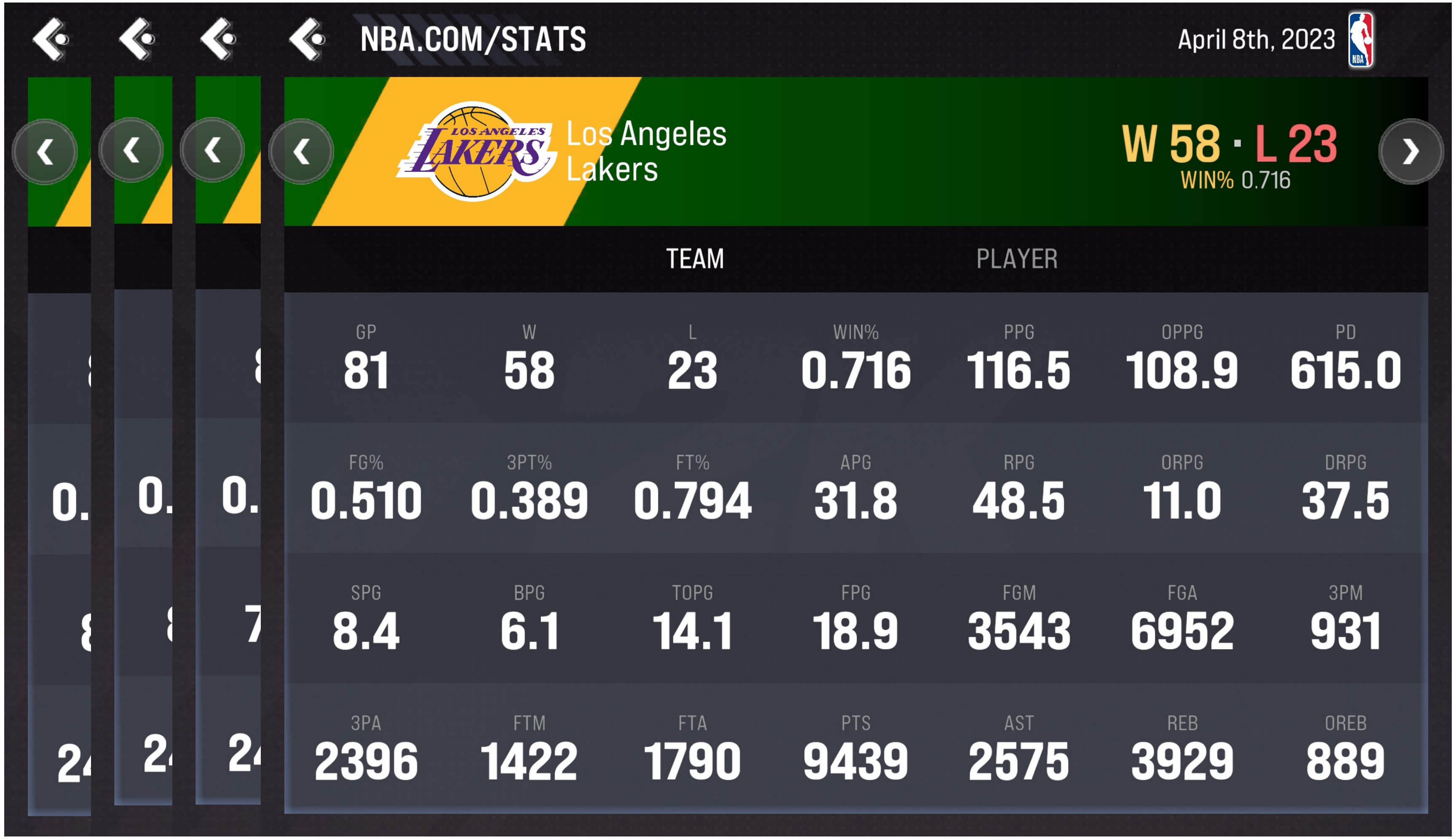
Test results:



Model IV : Open-source stochastic simulation machine for testing.

If we do **change** the lineup of Lakers: average winning rate for Lakers is **64.085%.**

Test results:



Model IV : Open-source stochastic simulation machine for testing.

Stochastic Simulation Results:

No. of Test	coef	std err	t value	P>|t|	[0.025	0.975]
Intercept	48.3019	1.813	26.638	0	44.492	52.111
x_reg	0.3721	0.049	7.580	0	0.269	0.475

OLS Regression Results:

	coef	std err	t value	P>|t|	[0.025	0.975]
Intercept	48.3019	1.813	26.638	0	44.492	52.111
x_reg	0.3721	0.049	7.580	0	0.269	0.475

Omnibus	5.695	**Durbin-Watson**	1.166	**Skew**	1.088	**Prob(JB)**	0.136
Prob(Omnibus)	0.058	**Jarque-Bera(JB)**	3.990	**Kurtosis**	3.239	**Cond. No.**	220

T-test result: t-statistic is: -10.2461 ; p-value is: 1.801^10
Therefore, we can reject the hypothesis.
Conclusion: Winning rate has been significantly improved after our change of lineup.

PART 05 Limitation

Limitation I: Player

Physical

Injury risk before and during a game

- Goes off injured
- Takes the field because a teammate is injured

Mental

Personal experiences and character

- Radical or Conservative
- Warriors' James Wiseman

Sentimental management

- Cohesive rhetoric
- Atmosphere in the locker room, rest areas
- People outside the arena

Cooperation and tactical awareness

- Uncountable data: "running to draw the defense”
- Subjective conclusions: assisted defense

The idea is not to block every shot. The idea is to make your opponent believe that you might block every shot.

——Bill Russell

Limitation II & III: League and Coach & Hardware Facility

Diversity and instability from…

League

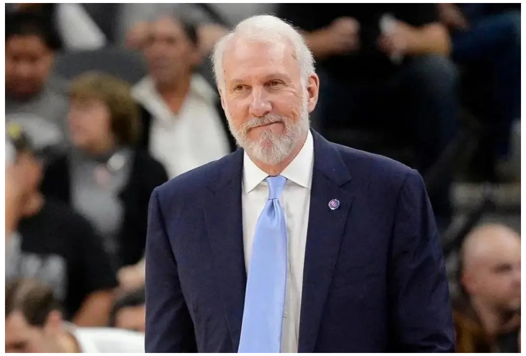
- Training and playing styles of different leagues

Coach

- Tactics and systems used in training and games
- Status of the coach during the games

Hardware Facilities

- Venues
- Facilities
- Equipment



Coaching

Limitation IV: Social Listening

Affect the performance of players who are with high expectations as well as self-denial.

Within and Between the team

- **Effect of amplification:** Amplify conflicts. Lead to team infighting and gaps.
- **Comparison/Evaluation** of the player's performance or weaknesses to other players
- **Unfavorable gossip**


Report: Draymond Green's Punch Knocked Jordan Poole Out

Stephen A. Smith reported that Poole was knocked out by Green's punch

JOEY LINN • OCT 12, 2022 8:24 PM EDT

PART 06 Conclusion

Key findings, Strategies and Suggestions

Exploratory Data Analysis

Methodology

- Machine Learning
- Data Mining
- Classification
- Decision Tree
- Stochastic simulation

Data Inspection & Evaluation

- Data source & validity

Model Construction

Model I : Machine Learning----Prediction of player's ability

Model II : Lakers Problem

Shooting Conclusion

Dribble Analysis

Defense Conclusion

Model III : Classification

Player Ability Indicators

Decision Tree —— Player Arbitrage Model

Model IV : Open-source stochastic simulation machine for testing

Optimized player selection

Suggestions

Limitation

Player: physical, mental

League and Coach & Hardware Facility

Social Listening

Whether it can succeed in reality

If modeling can be used to achieve optimization, why are there so many bad teams?

Subjective & objective

- The NBA is like a major league team that needs to be regulated .
- Draft Rules.
- Theme color makes PPT more convenient to change.
- Team Manager & players Decision.
- Degree of cooperation & Luck.

Whether NBA is a zero sum game?

Business and Sports Competition.

- Commercial value.
- Win win business.
- Victory or defeat.
- Team Ranking.

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Everyday

THANK YOU !

Appendix: Data Source

Player Data: https://www.nba.com/stats/players

Team Data: https://www.nba.com/stats/teams

Glossary Data: https://www.nba.com/stats/help/glossary

Stochastic Simulator: https://nba.2k.com/2k23/

Appendix

Model One Core Algorithm: 1- Data Import

```
score_22 = pd.read_excel("MGT_DATA/score_2K22.xlsx", engine="openpyxl")
salary_2021_2022 = pd.read_excel("MGT_DATA/All_Salary(2021-2022).xlsx", engine="openpyxl")
salary_2021_2022.columns = ['Index','PLAYER','Salary','Adjusted_Salary']
bio_data_21_22 = pd.read_excel("MGT_DATA/Bio_Info(2021-2022).xlsx", engine="openpyxl")

bio_data_21_22.rename(columns={'PLAYERS':'PLAYER'},inplace = True)
score_22.rename(columns={'PLAYERS':'PLAYER'},inplace = True)
df_trad = pd.read_csv("PLAYER_FIT/Traditional_Player(2021-2022) - Sheet1.CSV")
df_adva = pd.read_csv("PLAYER_FIT/Advanced_Player(2021-2022) - Sheet1.CSV")
df_misc = pd.read_csv("PLAYER_FIT/Misc_Player(2021-2022) - Sheet1.CSV")
```

```
df = pd.merge(df_trad, df_adva, on = 'PLAYER')
df = pd.merge(df, df_misc, on = 'PLAYER')
regr_df = df.loc[df['GP_x'] >= 20]
include_salary_df =  pd.merge(regr_df, salary_2021_2022,on = 'PLAYER')
include_bio_df =  pd.merge(include_salary_df, bio_data_21_22,on = 'PLAYER')
include_rating_df =  pd.merge(include_bio_df, score_22,on = 'PLAYER')
final_21_22_df = include_rating_df
height_lst = []
for k in range(0,final_21_22_df.shape[0]):
    s = final_21_22_df['HEIGHT'][k]
    lst = s.split('-')
    height = (float(lst[0])*12 + float(lst[1]))*2.54
    height_lst.append(height)
final_21_22_df['Height'] = pd.array(height_lst)
regr_df = final_21_22_df
```

Appendix

Model One Core Algorithm: 2- Bagging Model Fit

```
features_df = regr_df.apply(lambda x: (x - np.min(x)) / (np.max(x) - np.min(x)))
```

```
from sklearn.ensemble import BaggingRegressor
x_train,x_test,y_train,y_test = train_test_split(features_df,labels,test_size=0.2)
clf = BaggingRegressor()
rf = clf.fit (x_train, y_train.ravel())
y_pred = rf.predict(x_test)
print("BaggingRegressor Result: ")
print("Train Score: ",rf.score(x_train,y_train))
print("Test Score: ",rf.score(x_test,y_test))
```

```
BaggingRegressor Result:
Train Score:  0.9524326813686248
Test Score:  0.7436796048289227
```

Appendix

Model One Core Algorithm: 2- Score Prediction

```
features_df = regr_df
```

```
val = []
for t in range(features_df.shape[0]):
    x = features_df.loc[t,:].tolist()
    test_lst =[[]]*len(x)
    for k in range(0,len(x)):
        test_lst[k].append(x[k])
    test_array = np.array(test_lst)
    y_pred = rf.predict(test_array)[0]
    val.append(y_pred)
```

```
regr_df = pd.DataFrame()
regr_df['Predicted_Score'] = np.array(val)
regr_df['Player'] = PLAYER
new_index = np.array(list(range(1,regr_df.shape[0]+1)))
regr_df.set_index(new_index, inplace=True)
score_df = regr_df.sort_values(by = 'Predicted_Score', ascending = False)
```

```
score_df.to_excel("Score.xlsx")
```

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
1	Luka Doncic	92.3
2	Joel Embiid	91.9
3	Giannis Antetokounmpo	91.8
4	Donovan Mitchell	91.3
5	Stephen Curry	91.3
6	Damian Lillard	90.7
7	Pascal Siakam	90.2
8	Jayson Tatum	90.1
9	James Harden	90
10	Shai Gilgeous-Alexander	90
11	Nikola Jokic	89.8
12	Trae Young	89.2
13	Ja Morant	89.2
14	Anthony Davis	89
15	Kyrie Irving	89

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
16	Kevin Durant	88.9
17	Darius Garland	88.7
18	Paul George	88.7
19	Devin Booker	88.6
20	De'Aaron Fox	88.2
21	Domantas Sabonis	88.1
22	Desmond Bane	87.8
23	Karl-Anthony Towns	87.8
24	DeMar DeRozan	87.6
25	Jaylen Brown	87.1
26	Kristaps Porzingis	87
27	Jimmy Butler	86.8
28	LeBron James	86.7
29	Brandon Ingram	86.5
30	Jalen Brunson	86.4

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
31	Bam Adebayo	86.3
32	Myles Turner	86.1
33	Tyrese Haliburton	86
34	Jrue Holiday	84.5
35	Bradley Beal	84.3
36	Julius Randle	84.2
37	Jalen Green	83.9
38	Jerami Grant	83.8
39	Lauri Markkanen	83.6
40	Dejounte Murray	83.3
41	Brook Lopez	83.3
42	Zach LaVine	83.3
43	Nikola Vucevic	82.5
44	Rudy Gobert	82.2
45	Tyler Herro	82.1

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
46	Anthony Edwards	82
47	Scottie Barnes	81.8
48	Fred VanVleet	81.8
49	CJ McCollum	81.7
50	Russell Westbrook	81.6
51	Chris Paul	81.6
52	Cade Cunningham	81.5
53	Jarrett Allen	81.4
54	Kyle Kuzma	81.3
55	Andrew Wiggins	81.3
56	Jakob Poeltl	81.3
57	Anfernee Simons	81.3
58	Tyrese Maxey	81.3
59	Devin Vassell	81.1
60	Alperen Sengun	81.1

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
61	Terry Rozier	81
62	Mikal Bridges	80.9
63	Josh Giddey	80.7
64	Clint Capela	80.7
65	Keldon Johnson	80.7
66	Evan Mobley	80.5
67	Franz Wagner	80.4
68	Tobias Harris	80.3
69	LaMelo Ball	80.3
70	Gordon Hayward	80.2
71	Aaron Gordon	79.7
72	Cameron Johnson	79.7
73	Kyle Lowry	79.5
74	Thomas Bryant	79.4
75	D'Angelo Russell	79.3

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
76	Jaden McDaniels	79.1
77	Tre Mann	79
78	Spencer Dinwiddie	79
79	Jordan Clarkson	79
80	Bojan Bogdanovic	79
81	Alec Burks	78.9
82	De'Andre Hunter	78.9
83	Buddy Hield	78.9
84	Kevon Looney	78.8
85	Steven Adams	78.8
86	Malik Beasley	78.8
87	Chris Boucher	78.7
88	Jalen Suggs	78.7
89	Malcolm Brogdon	78.7
90	Dillon Brooks	78.7

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
91	Saddiq Bey	78.7
92	Derrick White	78.6
93	Reggie Jackson	78.6
94	Kentavious Caldwell-Pope	78.6
95	Malik Monk	78.6
96	Bobby Portis	78.6
97	Deandre Ayton	78.6
98	Nick Richards	78.5
99	Jonas Valanciunas	78.5
100	Harrison Barnes	78.5
101	Max Strus	78.5
102	Delon Wright	78.4
103	Jalen Smith	78.4
104	RJ Barrett	78.4
105	Kelly Olynyk	78.4

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
106	Christian Wood	78.4
107	Marcus Smart	78.3
108	Caris LeVert	78.3
109	Ayo Dosunmu	78.2
110	Draymond Green	78.2
111	Luguentz Dort	78.2
112	Isaiah Stewart	78.1
113	Mason Plumlee	78.1
114	De'Anthony Melton	78.1
115	John Collins	78.1
116	Kevin Love	78.1
117	Eric Gordon	78.1
118	Bol Bol	78
119	Jusuf Nurkic	78
120	Monte Morris	78

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
121	Tre Jones	78
122	Josh Hart	78
123	Jordan Poole	77.9
124	Ivica Zubac	77.9
125	Bruno Fernando	77.9
126	Kevin Huerter	77.8
127	Andre Drummond	77.8
128	Mike Conley	77.8
129	Bruce Brown	77.7
130	Bones Hyland	77.7
131	Cole Anthony	77.7
132	Aleksej Pokusevski	77.7
133	Collin Sexton	77.6
134	Rui Hachimura	77.6
135	Al Horford	77.6

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
136	Royce O'Neale	77.6
137	Zach Collins	77.5
138	Cameron Payne	77.4
139	Klay Thompson	77.3
140	John Konchar	77.2
141	Immanuel Quickley	77.2
142	Tyus Jones	77.1
143	Justise Winslow	77.1
144	Jalen McDaniels	77.1
145	Jevon Carter	77
146	Grant Williams	77
147	Mitchell Robinson	77
148	Norman Powell	76.8
149	Dean Wade	76
150	Jordan Nwora	76

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
151	Precious Achiuwa	76
152	Jae'Sean Tate	75.8
153	Jeff Green	75.7
154	Mo Bamba	75.6
155	Daniel Gafford	75.6
156	Mike Muscala	75.6
157	Xavier Tillman	75.5
158	Isaiah Roby	75.4
159	Kyle Anderson	75.4
160	Dewayne Dedmon	75.4
161	Chimezie Metu	75.4
162	Damian Jones	75.4
163	Yuta Watanabe	75.3
164	Rudy Gay	75.3
165	Seth Curry	75.3

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
166	Dwight Powell	75.2
167	Obi Toppin	75.1
168	Udoka Azubuike	75.1
169	Day'Ron Sharpe	75
170	Trey Lyles	75
171	Jeremiah Robinson-Earl	75
172	George Hill	75
173	Naji Marshall	74.9
174	Cedi Osman	74.9
175	Jonathan Kuminga	74.9
176	JaVale McGee	74.9
177	Maxi Kleber	74.9
178	Will Barton	74.9
179	Josh Green	74.9
180	Nicolas Batum	74.8

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
181	Paul Reed	74.8
182	Jalen Johnson	74.8
183	Willy Hernangomez	74.6
184	Nerlens Noel	74.6
185	Alex Caruso	74.5
186	Richaun Holmes	74.5
187	Killian Hayes	74.5
188	Goga Bitadze	74.5
189	Usman Garuba	74.5
190	Cam Reddish	74.5
191	Markieff Morris	74.5
192	Deni Avdija	74.5
193	Robin Lopez	74.4
194	DeAndre Jordan	74.4
195	Robert Covington	74.3

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
196	Darius Bazley	74.3
197	Dorian Finney-Smith	74.3
198	Onyeka Okongwu	74.3
199	Gorgui Dieng	74.2
200	Grayson Allen	74.2
201	Serge Ibaka	74.2
202	Javonte Green	74.2
203	Patrick Beverley	74.2
204	Terrence Ross	74.2
205	Doug McDermott	74.2
206	Damion Lee	74.2
207	Josh Richardson	74.2
208	Jaylen Nowell	74.2
209	Taj Gibson	74.2
210	Boban Marjanovic	74.2

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
211	Cam Thomas	74.1
212	Torrey Craig	74.1
213	Terence Davis	74.1
214	Juan Toscano-Anderson	74.1
215	Kenrich Williams	74.1
216	Brandon Clarke	74.1
217	Blake Griffin	74.1
218	James Johnson	74
219	Naz Reid	74
220	Isaiah Jackson	74
221	Gabe Vincent	74
222	Shake Milton	74
223	Thaddeus Young	73.9
224	Moses Brown	73.9
225	Davion Mitchell	73.9

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
226	Gary Harris	73.9
227	Wenyen Gabriel	73.8
228	Dalano Banton	73.8
229	Georges Niang	73.8
230	JaMychal Green	73.7
231	Kai Jones	73.7
232	Drew Eubanks	73.7
233	Keita Bates-Diop	73.6
234	Patrick Williams	73.6
235	Duncan Robinson	73.6
236	Chuma Okeke	73.6
237	Goran Dragic	73.6
238	Aaron Nesmith	73.5
239	Malachi Flynn	73.5
240	Nassir Little	73.5

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
241	Taurean Prince	73.4
242	Donte DiVincenzo	73.4
243	Evan Fournier	73.4
244	Chris Duarte	73.3
245	Frank Kaminsky	73.3
246	Payton Pritchard	73.3
247	Anthony Lamb	73.3
248	Khem Birch	73.3
249	Davis Bertans	73.2
250	Montrezl Harrell	73.2
251	Corey Kispert	73.2
252	Coby White	73.2
253	Terance Mann	73.1
254	Tony Bradley	73.1
255	Mamadi Diakite	73.1

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
256	Isaiah Livers	73.1
257	Keon Johnson	73.1
258	Josh Christopher	73.1
259	Reggie Bullock	73.1
260	Derrick Rose	73.1
261	Luke Kennard	73
262	Talen Horton-Tucker	73
263	Anthony Gill	73
264	Lamar Stevens	73
265	Hamidou Diallo	72.9
266	Landry Shamet	72.8
267	Theo Maledon	72.8
268	Zeke Nnaji	72.8
269	Joe Harris	72.7
270	Furkan Korkmaz	72.7

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
271	Quentin Grimes	72.7
272	Udonis Haslem	72.7
273	Cory Joseph	72.7
274	Justin Holiday	72.7
275	JT Thor	72.7
276	Nickeil Alexander-Walker	72.6
277	Garrett Temple	72.6
278	James Bouknight	72.6
279	Jaxson Hayes	72.6
280	Vlatko Cancar	72.6
281	Oshae Brissett	72.6
282	Miles McBride	72.5
283	Isaiah Joe	72.4
284	Facundo Campazzo	72.4
285	Aaron Holiday	72.3

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
286	Raul Neto	72.2
287	Jaden Springer	72.2
288	KZ Okpala	72.2
289	Ty Jerome	72.2
290	Matisse Thybulle	72.2
291	Thanasis Antetokounmpo	72.1
292	Rodney McGruder	72.1
293	Trent Forrest	72.1
294	Josh Okogie	72.1
295	Leandro Bolmaro	72.1
296	Isaac Okoro	72.1
297	Alex Len	72
298	Isaiah Todd	71.7
299	Bryn Forbes	71.7
300	Austin Rivers	71.6

Appendix

Model One Results: All Players Predicted Score in 2022-2023

Rank	Player Name	Predicted Score For this Season
301	Moses Moody	71.4
302	Jarrett Culver	71.2
303	Romeo Langford	71.2
304	Nathan Knight	71
305	Marko Simonovic	70.5
306	Cody Martin	69.3

Appendix

Model Two: Rank Algorithm

```
def judge_rank(sorted_df, rank_condition):
    sorted_df = sorted_df.sort_values(by = rank_condition, ascending = False )
    new_index = np.array(list(range(1,31)))
    sorted_df.set_index(new_index, inplace=True)
    rank = sorted_df.loc[sorted_df['TEAM']=='Los Angeles Lakers'].index.tolist()[0]

    return rank
for k in df.columns.values.tolist()[3:]:
    print('The rank of '+k+' is '+str(judge_rank(df, k)))
```

```
Season 2022-2023:
The rank of PTS is 29
The rank of FGM is 29
The rank of FGA is 23
The rank of FG% is 30
The rank of 3PM is 29
The rank of 3PA is 22
The rank of 3P% is 30
The rank of EFG% is 30
```

Appendix

Model Three Core Algorithm: 1- Classification of Player Ability Indicators

```
# Classification
def allocate_slice(df,index):
    quan = df[index].describe(percentiles = perc)
    quan = quan.iloc[4:13]
    df[index+'_allo'] = 0
    df.loc[df[index] <= quan[0],index+'_allo'] = 1
    df.loc[(df[index] > quan[0])&(df[index] <= quan[1]),index+'_allo'] = 2
    df.loc[(df[index] > quan[1])&(df[index] <= quan[2]),index+'_allo'] = 3
    df.loc[(df[index]> quan[2])&(df[index] <= quan[3]),index+'_allo'] = 4
    df.loc[(df[index] > quan[3])&(df[index] <= quan[4]),index+'_allo'] = 5
    df.loc[(df[index] > quan[4])&(df[index] <= quan[5]),index+'_allo'] = 6
    df.loc[(df[index]> quan[5])&(df[index] <= quan[6]),index+'_allo'] = 7
    df.loc[(df[index] > quan[6])&(df[index] <= quan[7]),index+'_allo'] = 8
    df.loc[(df[index] > quan[7])&(df[index] <= quan[8]),index+'_allo'] = 9
    df.loc[df[index] > quan[8],index+'_allo'] = 10
    return df
```

Appendix

Model Three Core Algorithm: 2- Finding the worst n LAKERS' players based on the target indicators

```
def rank(sorted_df, rank_condition):
    sorted_df = sorted_df.sort_values(by = rank_condition, ascending = False )
    new_index = np.array(list(range(1,15)))
    sorted_df.set_index(new_index, inplace=True)
    sorted_df[rank_condition+'_score'] = -new_index
    return sorted_df
```

```
def the_worse_players(sorted_df, n, indexs):
    sorted_df['Score'] = 0
    for k in indexs:
        sorted_df = rank(sorted_df, k)
        sorted_df['Score'] += sorted_df[k+'_score']
    sorted_df = sorted_df.sort_values(by = 'Score', ascending = False )
    players = sorted_df.tail(n)
    return players['PLAYER'].tolist()
```

Appendix

Model Three Core Algorithm: 2- Finding the worst n LAKERS' players based on the target indicators

```python
def rank(sorted_df, rank_condition):
    sorted_df = sorted_df.sort_values(by = rank_condition, ascending = False )
    new_index = np.array(list(range(1,15)))
    sorted_df.set_index(new_index, inplace=True)
    sorted_df[rank_condition+'_score'] = -new_index
    return sorted_df
```

```python
def the_worse_players(sorted_df, n, indexs):
    sorted_df['Score'] = 0
    for k in indexs:
        sorted_df = rank(sorted_df, k)
        sorted_df['Score'] += sorted_df[k+'_score']
    sorted_df = sorted_df.sort_values(by = 'Score', ascending = False )
    players = sorted_df.tail(n)
    return players['PLAYER'].tolist()
```

Appendix

Model Four: 1-Original / After-Change Lineups Win Rate

	Original Lineups Win Rate	After-Change Lineups Win Rate
0	54.3	71.6
1	53.1	71.6
2	53.1	66.7
3	51.9	66.7
4	51.9	66.7
5	51.9	66.7
6	46.9	64.2
7	46.9	64.2
8	46.9	64.2
9	39.5	64.2
10	39.5	64.2
11	39.5	63.0
12	39.5	63.0
13	38.3	63.0
14	38.3	61.7
15	38.3	61.7
16	30.9	61.7
17	30.9	59.3
18	30.9	59.3
19	25.9	58.0

Appendix

Model Four: 2-Regression Algorithm and Result

```
df.columns = ['x_reg', 'y_reg']
```

```
reg_HAC = smf.ols(formula=' y_reg ~ x_reg', data=df)
results_HAC =reg_HAC.fit(cov_type='HAC', use_t=True,cov_kwds={'maxlags':1})
results_HAC.summary()
```

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	48.3019	1.813	26.638	0.000	44.492	52.111
x_reg	0.3721	0.049	7.580	0.000	0.269	0.475

Omnibus:	5.695	**Durbin-Watson:**	1.166
Prob(Omnibus):	0.058	**Jarque-Bera (JB):**	3.990
Skew:	1.088	**Prob(JB):**	0.136
Kurtosis:	3.239	**Cond. No.**	220.

Relationship is far away from expected y = x

Appendix

Model Four: 3-T-test Algorithm and Result

```
data1 = df['x_reg']
data2 = df['y_reg']
(statistic, pvalue) = stats.ttest_ind(data1,data2,equal_var=False)
print("t statistic is: ", statistic)
print("pvalue is: ", pvalue)
```

```
t statistic is:  -10.246175502264531
pvalue is:  1.801075810484235e-10
```

Rejects the null hypothesis; the changed win rate is significantly higher

Appendix: Glossary

- **FG%: Field Goal Percentage:** The percentage of field goal attempts that a player makes
- **3P%: Three Point Field Goal Percentage:** The percentage of 3-point field goal attempts that a player makes
- **EFG%: Effective Field Goal Percentage:** Measures field goal percentage adjusting for made 3-point field goals being 1.5 times more valuable than made 2-point field goals.
- **Field Goals Made:** The number of field goals that a player or team has made, including both 2 pointers and three-pointers.
- **Field Goals Attempted:** The number of field goals that a player or team has attempted. This includes both 2 pointers and three-pointers.
- **Field Goal Percentage:** The percentage of field goal attempts that a player makes.
- **3 Point Field Goals Attempted:** The number of 3 point field goals that a player or team has attempted.
- **2 Point Field Goals Attempted:** The number of 2 point field goals that a player or team has attempted.
- **2 Point Field Goal Percentage:** The percentage of 2 point field goals that a player or team has attempted.
- **Passes Made:** The number of total passes made by a player or team per game
- **Passes Received:** The number of total passes received by a player or team per game
- **Assist to Pass Percentage:** The percentage of passes by a player or team that are assists
- **Assist to Pass Percentage Adjusted:** The percentage of passes by a player or team that are assists, free throw assists, or secondary assists

Appendix: Glossary

- **DEF RTG:** Defensive Rating
- **DREB:** Defensive Rebounds
- **DREB%:** Defensive Rebounds Percentage
- **STL:** Steals
- **BLK:** Blocks
- **OPP PTS OFF TOV:** Opponent Points Off Turnovers
- **OPP PTS 2ND CHANCE:** Opponent 2nd Chance Points
- **OPP PTS FB:** Opponent Fast Break Points
- **OPP PTS PAINT:** Opponent Points in the Paint
- **Freq (Frequency):** The number of events that occur that fits the specified criteria is based on the number of events overall.
- **DIFF% (Percentage Points Difference):** The difference between the normal percentage of a shooter on shots throughout the season and the percentage on shots when the defensive player or team is guarding the shooter. A negative value means better.