Passing Power: Social Network Insights for Scoring Success in the NBA

SNAP Team 21
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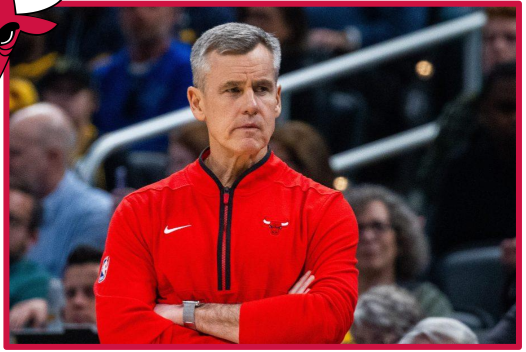
June 4, 2025

Client: Chicago Bulls

What network properties are associated with high team performance?

- Are successful teams more likely to have reciprocal passing ties between players?
- Are more evenly distributed pass networks more successful?

What metrics are correlated with the most success when recruiting new players?



Coach: Billy Donovan

GM: Marc Eversley

Data Landscape

nba_api

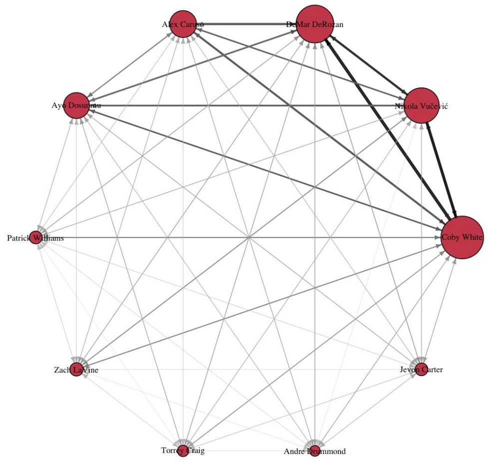
Top 10 players per team by total season minutes

2023-24, 2024-25 seasons

Passer	Receiver	Passes	Assists
Coby White	DeMar DeRozan	1077	69
Nikola Vučević	Coby White	999	55
Coby White	Nikola Vučević	859	114
DeMar DeRozan	Coby White	758	71
Alex Caruso	DeMar DeRozan	737	28
Nikola Vučević	DeMar DeRozan	732	40
DeMar DeRozan	Nikola Vučević	728	95
Alex Caruso	Coby White	672	35
Ayo Dosunmu	DeMar DeRozan	555	33
Ayo Dosunmu	Nikola Vučević	531	73
Alex Caruso	Nikola Vučević	488	75
Coby White	Ayo Dosunmu	469	53

30 teams in the NBA

2 seasons

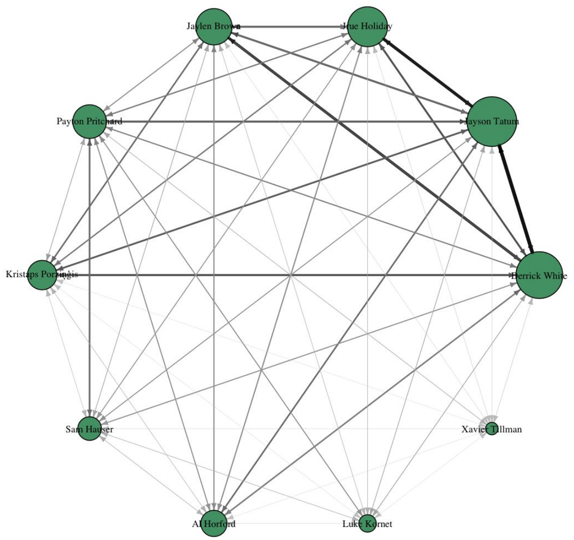


weighted, directed graph

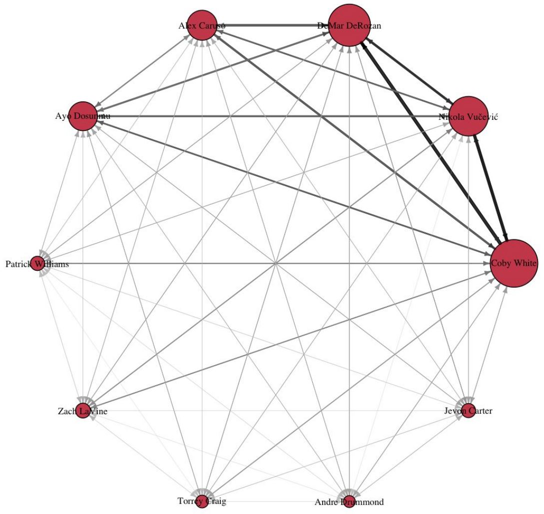
nodes = players
edges = passes with weights representing pass volume

Examples of Passing Networks

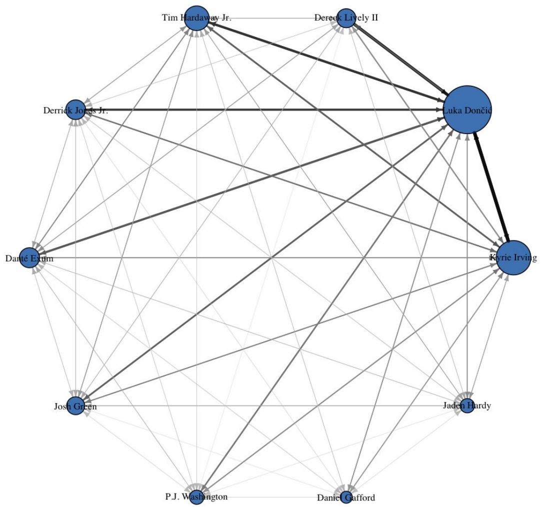
Boston Celtics Passes | 64 Wins | 1 Seed | 2023-24



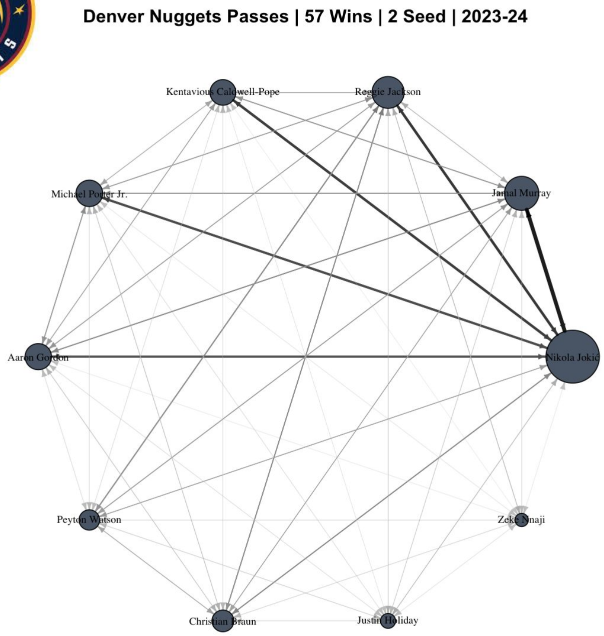
Chicago Bulls Passes | 39 Wins | 9 Seed | 2023-24



Dallas Mavericks Passes | 50 Wins | 5 Seed | 2023-24

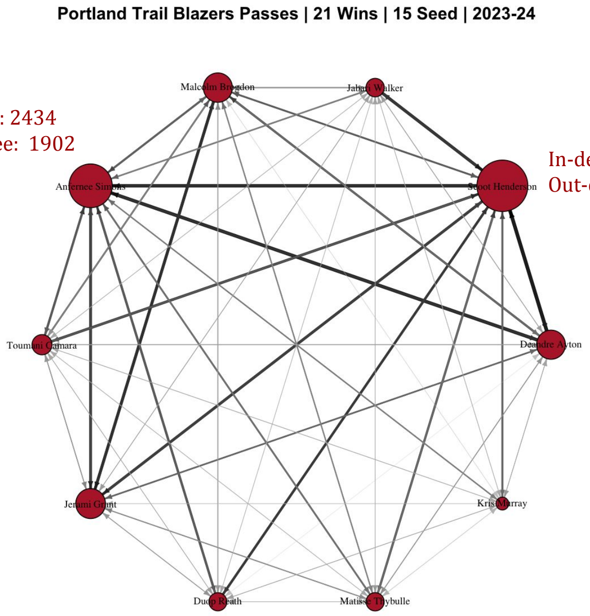


Star Player vs. Young Team Networks



Weighted
In-degree: 5019
Out-degree: 5553

star player (MVP Nikola Jokic) directs the offense



In-degree: 2434
Out-degree: 1902

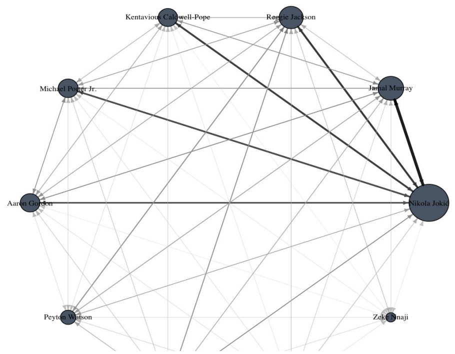
In-degree: 2714
Out-degree: 2391

young team, rebuilding after trading their star player (Damian Lillard)

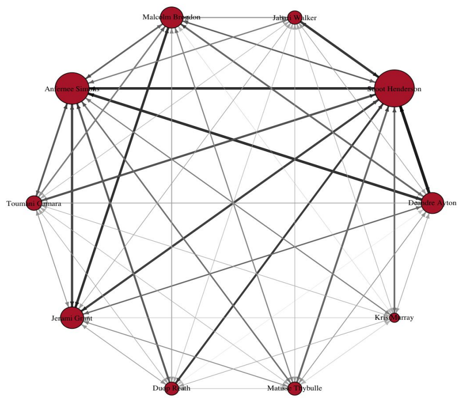
Passing vs Assist Networks

passing networks

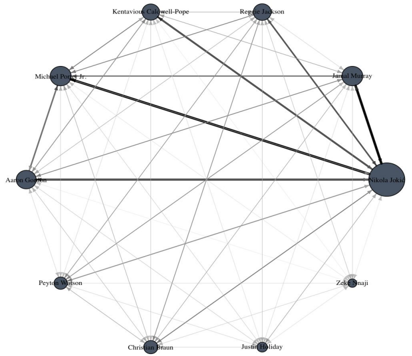
Denver Nuggets Passes | 57 Wins | 2 Seed | 2023-24



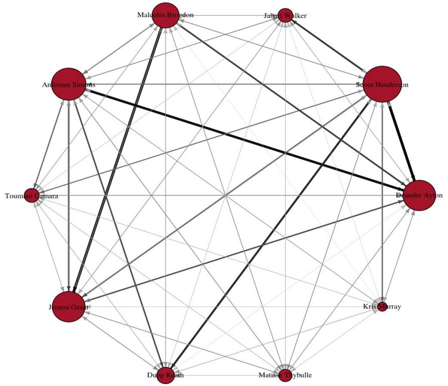
Portland Trail Blazers Passes | 21 Wins | 15 Seed | 2023-24



Denver Nuggets Assists | 57 Wins | 2 Seed | 2023-24

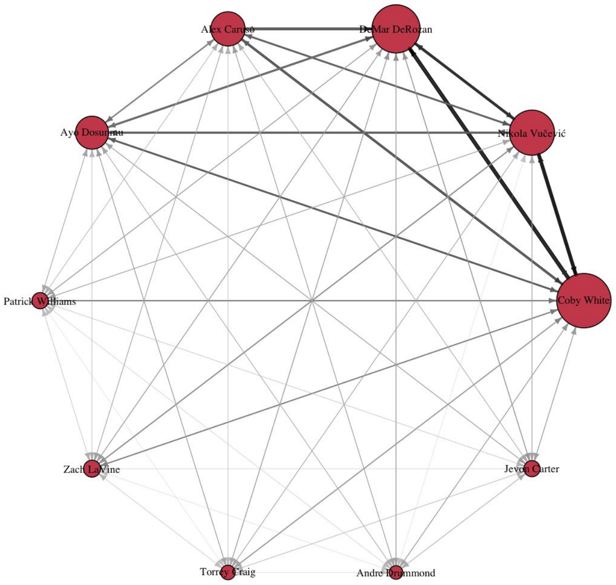


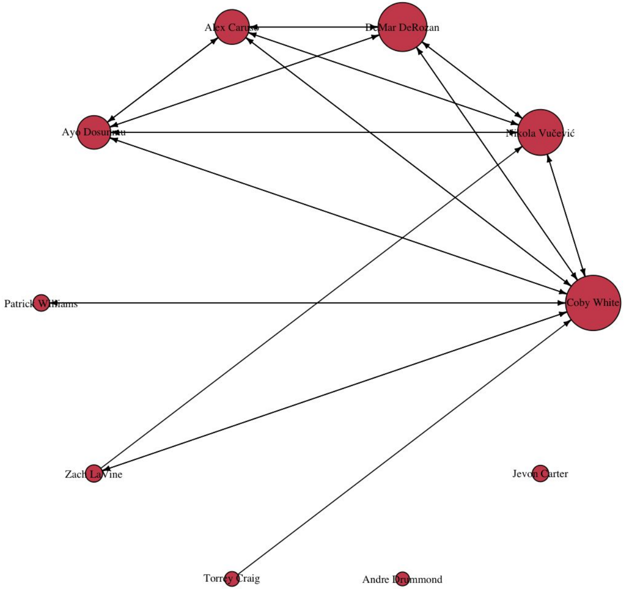
Portland Trail Blazers Assists | 21 Wins | 15 Seed | 2023-24



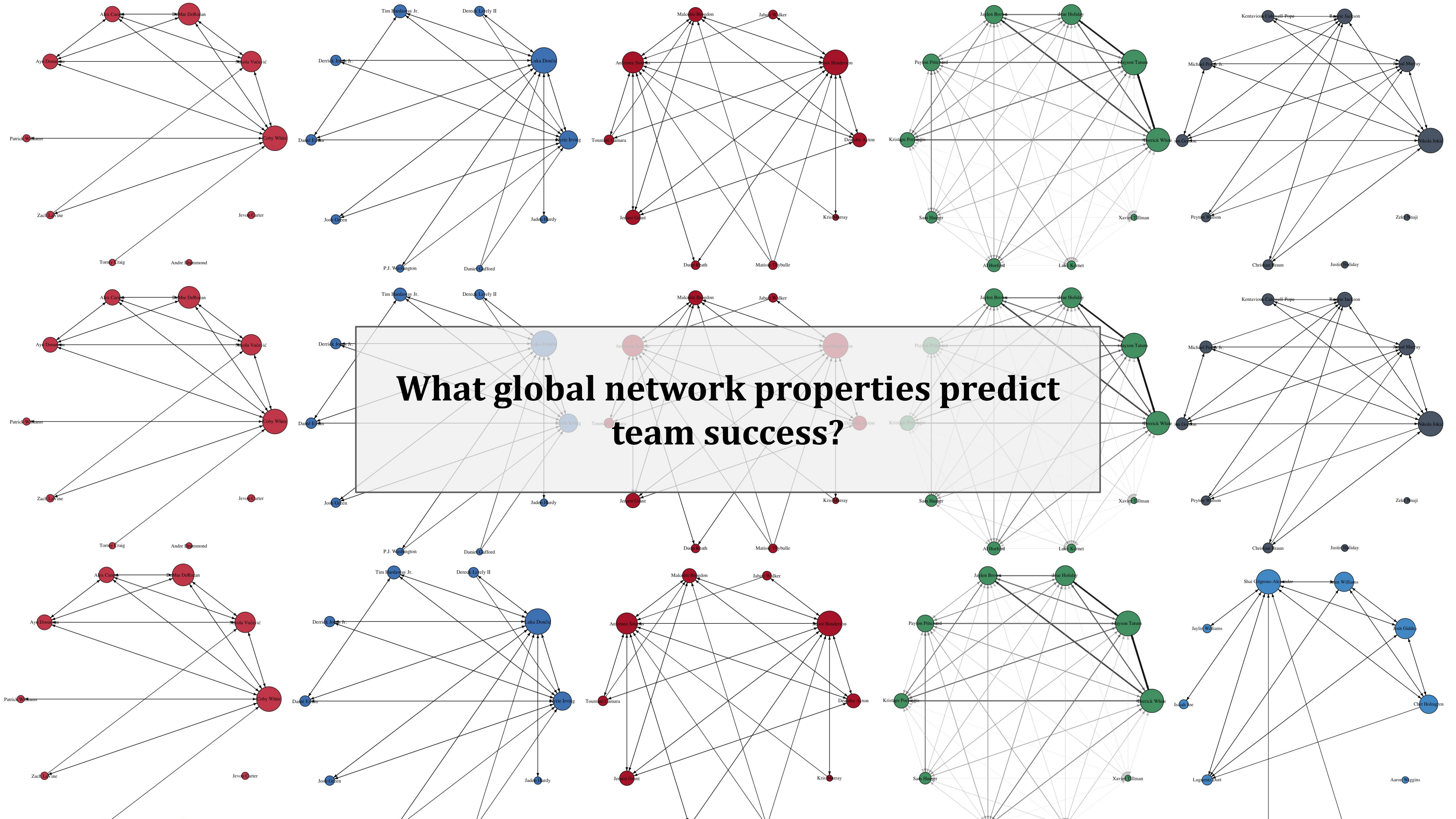
assist networks

Binarize



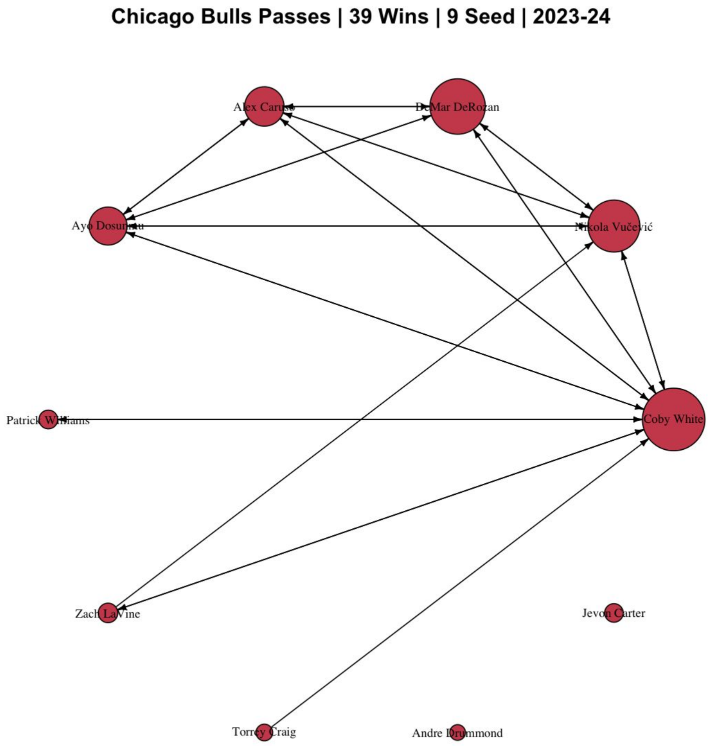



```r
mean_weight <- mean(E(g)$weight)
g <- delete_edges(g, E(g)[weight <= mean_weight])
E(g)$weight <- 1
```



What global network properties predict team success?

Global Network Properties



Wins	39
Seed	9
Nodes	10
Edges	26
Density	0.2889
Reciprocity	0.9231
Transitivity	0.66
AvgDegree	5.2
OutDegreeCentralization	0.3778
BetweennessCentralization	0.2963
AssortativityOut	-0.6142
AssortativityIn	-0.6245
AvgPathLength	1.47
Diameter	2

Results: Network Level Regression Analysis

Passing Networks:

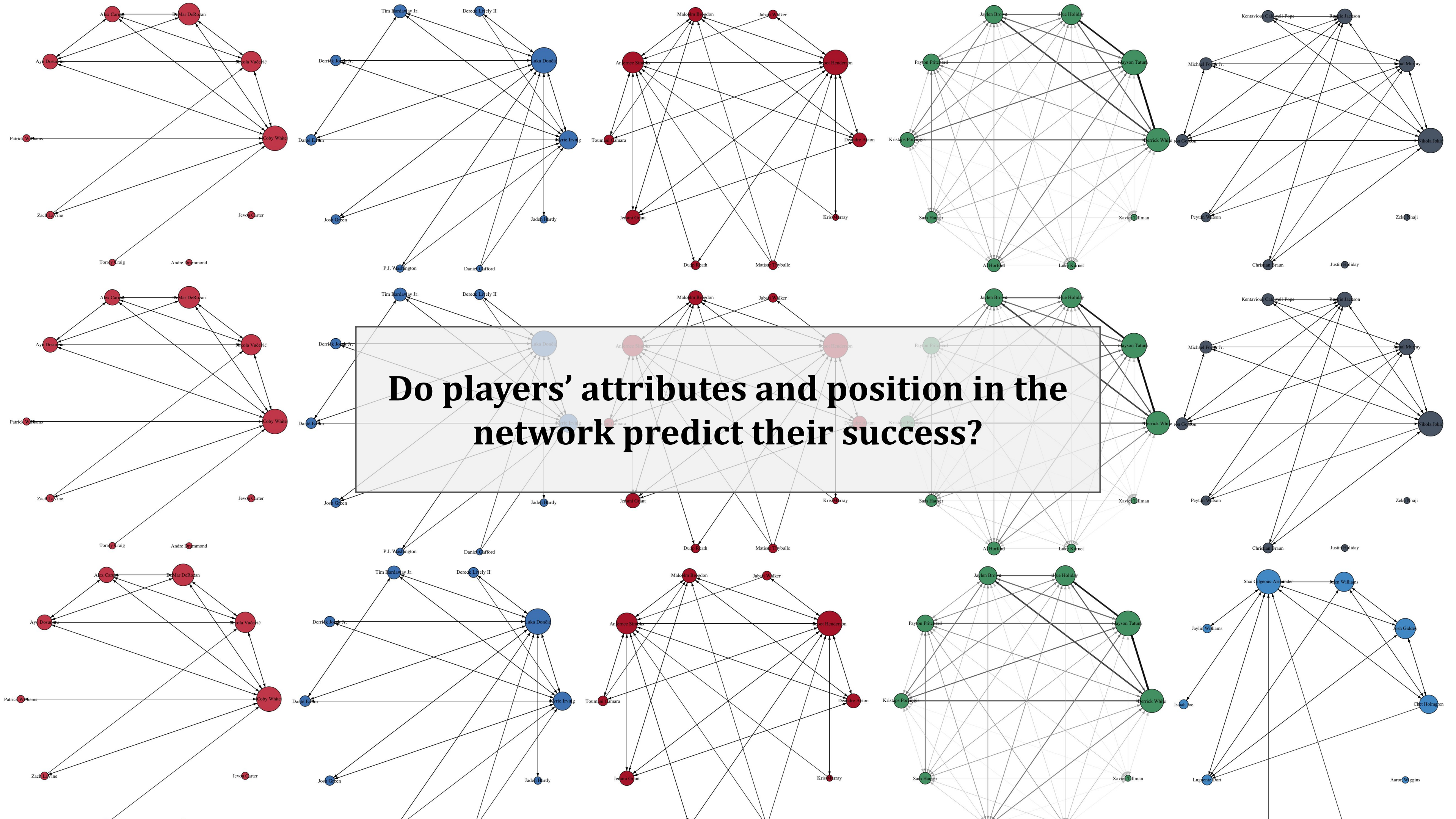
Edge Counts, Density, and Average Degree correlated with team success (p-value < 0.05)

Note: These properties are related since the networks have the same number of nodes (10 players)

Assist Networks:

Average Path Length predictive of more wins (p-value < 0.05)

```
cor.test(wins, metricP)
cor(wins, metricP)
```



Do players' attributes and position in the network predict their success?

Hypotheses

(high scoring = 20 points per game)

1. There is a negative contagion effect for high scoring.
2. Older players are more likely to be high scorers.
3. Players who have been on their current team longer are more likely to be high scorers.
4. Players who are drafted higher (selected earlier) are more likely to be high scorers.
5. Players who *pass* the ball with more teammates are more likely to be high scorers.
6. Players who *receive* the ball from more teammates are more likely to be high scorers.

ALAAM Analysis
(Attribute Data)

Continuous

- Points per Game (PPG)
- Age
- Years on current team
- Draft pick (1 → 61)

Binary

- First round pick
- In their "prime" (25 → 30)

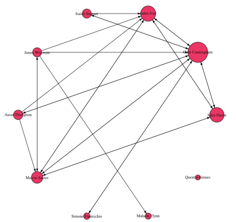
Player	PPG	age	tenure_years	guard	prime_age	first_round	draft_pick
Coby White	19.1	24	5	1	0	1	7
Nikola Vučević	18.0	34	4	0	0	1	16
DeMar DeRozan	24.0	35	3	1	0	1	9
Alex Caruso	10.1	30	3	1	1	0	61
Ayo Dosunmu	12.2	24	3	1	0	0	38
Patrick Williams	10.0	23	4	0	0	1	4
Zach LaVine	19.5	29	7	1	1	1	13
Torrey Craig	5.7	34	1	0	0	0	61
Andre Drummond	8.4	31	2	0	0	1	9
Jevon Carter	5.0	29	1	1	1	0	32
Jalen Johnson	16.0	23	3	0	0	1	20
Dejounte Murray	22.5	28	2	1	1	1	29
Bogdan Bogdanović	16.9	32	4	1	0	1	27
De'Andre Hunter	15.6	27	5	1	1	1	4
Trae Young	25.7	26	6	1	1	1	5
Saddiq Bey	13.7	25	2	1	1	1	19
Clint Capela	11.5	30	4	0	1	1	25

```
att_NBA$ppg_binary <- ifelse(att_NBA$"PPG" >= 20, 1, 0)
```

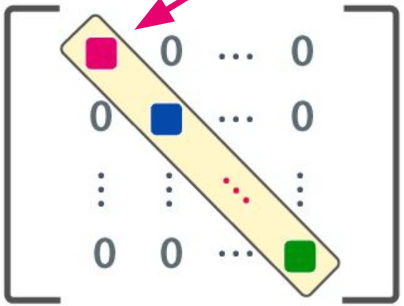
R

"high scorer" = 20 points per game

ALAAM Analysis
(Adjacency Matrix)

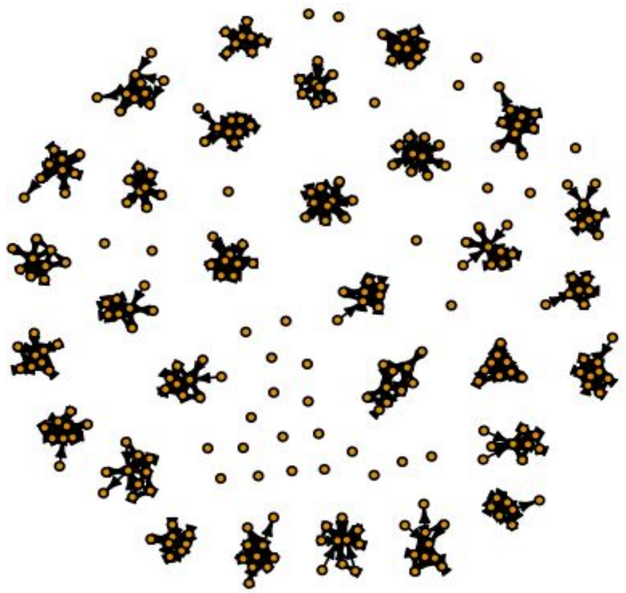


	JD	CC	JI	IS	JW	AT	MS	SF	MF	QG
JD	0	1	1	0	0	0	1	0	0	0
CC	1	0	1	1	0	1	1	1	0	0
JI	1	1	0	0	0	0	1	0	0	0
IS	0	1	1	0	0	0	0	0	0	0
JW	0	1	1	0	0	0	1	0	1	0
AT	0	1	1	0	0	0	1	0	0	0
MS	1	1	1	0	1	0	0	0	0	0
SF	0	1	0	0	0	0	0	0	0	0
MF	0	0	0	0	0	0	0	0	0	0
QG	0	0	0	0	0	0	0	0	0	0

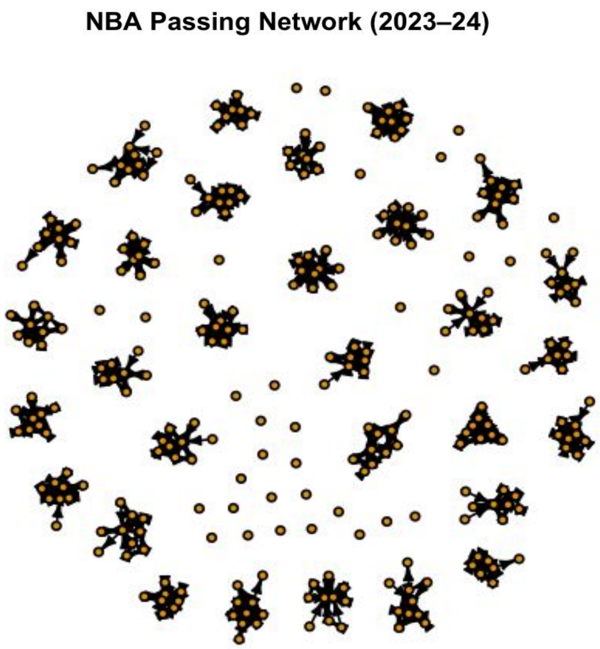


Teams in block diagonal for higher ESS

NBA Passing Network (2023–24)



ALAAM Analysis
(ESS)



The large ESS values (> 200) support the validity of the model.

```
you have done  40000  iterations out of  40000
theta: -10.256 -1.499 0.242 0.475 0.421 -1.228 -2.616 -0.059 -4.086 0.991 4.065 0.121
summaries of the posterior draws:
                          mean          sd          ESS      SACF 10      SACF 30
intercept          -10.42155678  7.06905748 377.77657666  0.81435423  0.55603966
contagion           -1.50596747  0.77597994 414.75080728  0.79715241  0.53430935
age                  0.18471364  0.17043303 423.47124719  0.78823030  0.49470771
tenure_years         0.49030949  0.33293813 399.70742053  0.80397339  0.53799461
guard               -2.73188886  1.96964808 342.36696296  0.82845406  0.56933987
prime_age            1.48010541  1.57299096 421.76473404  0.79154356  0.51388661
first_round         -1.07828417  3.80310083 286.01631723  0.85140366  0.62171738
draft_pick          -0.12468188  0.09763363 375.63616065  0.80747243  0.53222002
out.degree          -3.68504986  2.50078804 268.75547752  0.86612589  0.65989377
in.degree            2.28186567  0.98859751 407.55172553  0.80188634  0.54242886
reciprocity          2.73172101  2.36372490 332.65229170  0.83456831  0.59843948
transitive.triangles 0.13382643  0.28194685 258.74564357  0.86613406  0.65033567
```

ALAAM Results

(high scoring = 20 points per game)

1. **There is a negative contagion effect for high scoring.**
The 95% credibility interval for the contagion effect [-2.91, -0.157] does not include 0, so we can reject the null hypothesis. The negative estimate (-1.378) and odds-ratio of 0.252 means a player is about **75% less likely** to be high scoring if they are connected to others who do.

2. **Older players are more likely to be high scorers.**
Although the estimate is positive (0.166), the 95% credibility interval for the effect of age [-0.175, 0.543] includes 0, so the estimate is not conclusive. Therefore, we **FAIL** to reject the null hypothesis.

3. **Players who have been on their current team longer are more likely to be high scorers.**
Although the estimate is positive (0.466), the 95% credibility interval for the effect of team tenure [-0.097, 1.10] includes 0, so the estimate is not conclusive. As a result. we **FAIL** to reject the null hypothesis.

ALAAM Results

(high scoring = 20 points per game)

4. **Players who are drafted higher (selected earlier) are more likely to be high scorers.**
   Although the estimate is negative (-0.125), in the direction of our hypothesis, the 95% credibility interval for the effect of higher draft pick [-0.346, 0.044] includes 0, so the estimate is not conclusive. We **FAIL** to reject the null hypothesis.

5. **Players who pass the ball with more teammates are more likely to be high scorers.**
   The 95% credibility interval for the out.degree effect [-8.516, 0.231] (high standard deviation) includes 0, so the estimate is not conclusive and we **FAIL** to reject the null hypothesis. The estimate is negative (-3.302), in the opposite direction of our hypothesis.

6. **Players who receive the ball from more teammates are more likely to be high scorers.**
   The 95% credibility interval for the in.degree effect [0.647, 4.488] does not include 0, so we can REJECT the null hypothesis. Given the positive estimate (2.271), the odds-ratio of 9.689 means a player is about **869% more likely** to be high scoring if they receive the ball from more teammates.

Results: Goodness-of-Fit (gof) Test

The gof results indicate that our NBA model provides a satisfactory fit to the observed data.

```
Simulating GOF took  7.348319
Calculating statistics took  0.871665
                       obs      mean    p-val
intercept           50.000    48.654    0.153
simple cont.        44.000    41.028    0.165
recip cont.         22.000    20.148    0.151
indirect cont.     147.000   146.780    0.199
closedind cont.    143.000   131.778    0.164
transitive cont.    12.000    17.092    0.253
outdegree          243.000   230.548    0.110
indegree           293.000   274.628    0.087
reciprochation     238.000   226.274    0.114
instar             798.000   734.014    0.078
outstar            542.000   508.098    0.115
twopath           1306.000  1212.730    0.097
in3star           1296.000  1190.112    0.099
out3star           707.000   664.570    0.143
transitive         566.000   542.724    0.147
cyclic             617.000   584.874    0.111
indirect           731.000   708.300    0.158
excl.indirect       95.000   101.318    0.170
```

GOF p-values for the NBA model ranged from 0.078 to 0.253, with no values near 0 or 1. The absence of any p-values below 0.05 further supports the model’s overall adequacy.

Actionable Insights & Recommendations

Watch Out for Scoring Contagion (Negative Effect)

Insight:

A negative contagion effect shows that players connected to high scorers are about 75% less likely to be high scorers themselves (OR = 0.252).

Recommendations:

- **Avoid lineups overloaded with primary scorers**. Instead, spread them out so others stay aggressive.
- **Rethink rotations**. Players may defer to high scorers rather than developing confidence or asserting themselves. Consider developing second-unit lineups that let emerging scorers take more initiative. Encourage players in non-star roles to stay aggressive rather than defer automatically to top scorers.

Actionable Insights & Recommendations

Inbound Passing Drives Scoring

Insight:

Players who receive passes from more teammates are significantly more likely to be high scorers (odds ~9.7x higher).

Recommendations:

- **Design offensive plays that facilitate scorers from multiple positions on the court** (drive-and-kick, reverse ball screens, high-post hubs).
- **Encourage unselfish passing patterns** that enable scoring opportunities for a diverse set of players

Actionable Insights & Recommendations

Draft Status Isn't Everything: Prioritize Development

Insight:

While the data shows a slight negative relationship between draft position and scoring (i.e., higher picks tend to score more), the result is not statistically conclusive. This suggests that being a top draft pick may not be as predictive of scoring success as commonly assumed. Scoring success is likely influenced by role clarity, coaching, system fit, and opportunity, not only draft status.

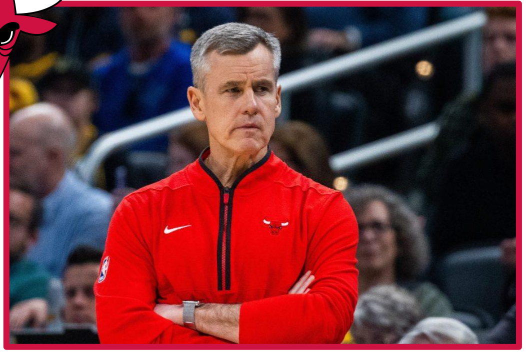
Recommendations:

- **Prioritize internal development systems** and performance analytics over draft pedigree
- Encourage a **longer-term view on player evaluation**

Final Takeaways

- Stagger top scorers across lineups.
- Encourage secondary players to stay aggressive rather than defer.
- Run plays that route passes to scorers from multiple teammates.
- Reinforce unselfish ball circulation.
- Create a culture where work ethic, skill progression, and basketball IQ outweigh draft pedigree in determining playing time and role elevation.

CHICAGO BULLS



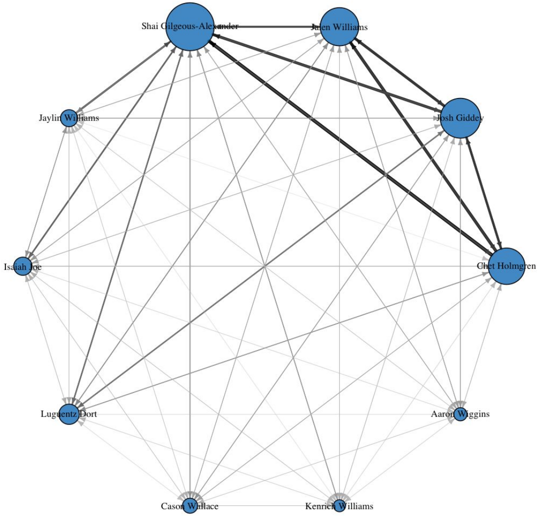
Coach: Billy Donovan

GM: Marc Eversley

Supplemental Slides

Passing Networks: Western Conference

Oklahoma City Thunder Passes | 57 Wins | 1 Seed | 2023-24



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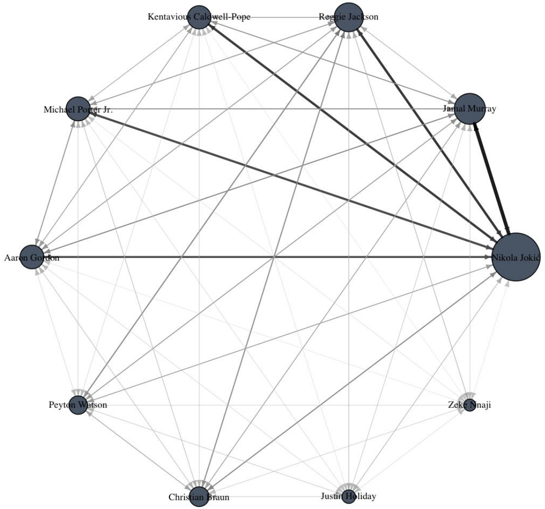

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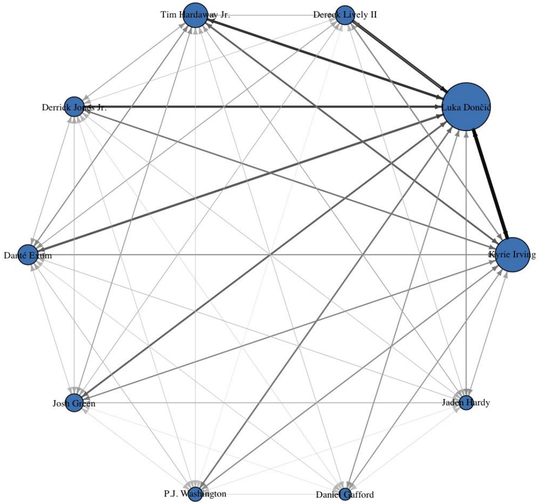
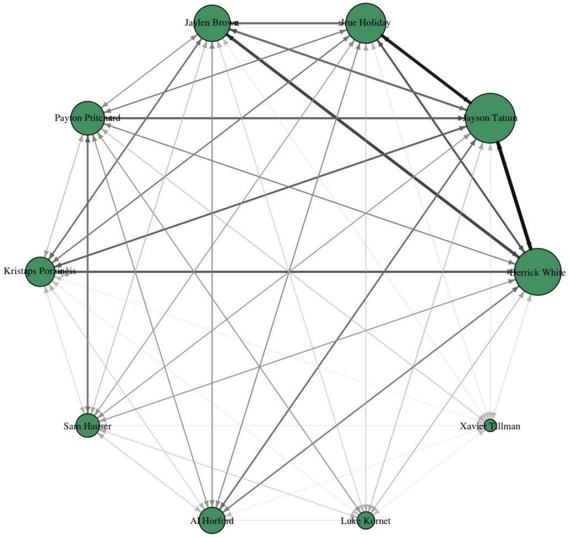
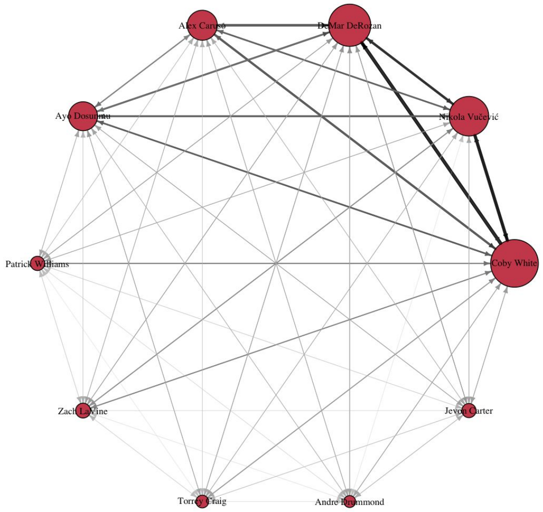


Passing Networks: Eastern Conference

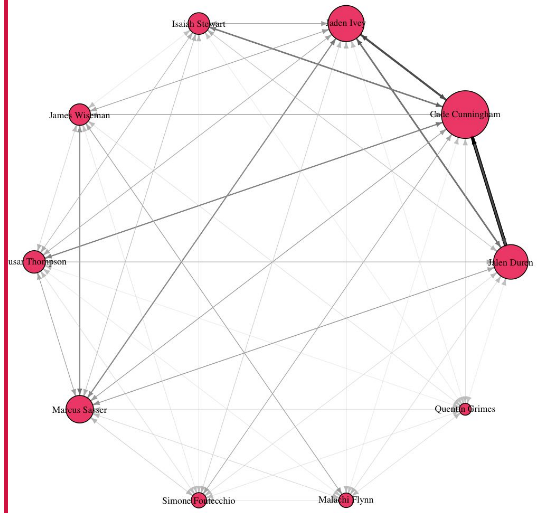
Boston Celtics Passes | 64 Wins | 1 Seed | 2023-24



Chicago Bulls Passes | 39 Wins | 9 Seed | 2023-24



Detroit Pistons Passes | 14 Wins | 15 Seed | 2023-24



ALAAM Analysis

Steps:

1. Binarize (mean) ✓
2. Define success
   high scorer = 20 points per game (PPG)
3. Improve low ESS of Chicago Bulls
   combine the entire league into a network*
4. Hypothesize
5. ALAAM!
6. Analyze results

Results: ALAAM

parameter	mean	sd	0.025	0.975
intercept	-9.953	6.949	-24.442	2.784
contagion	-1.378	0.713	-2.91	-0.157
age	0.166	0.18	-0.175	0.543
tenure_years	0.466	0.307	-0.097	1.1
guard	-2.736	1.845	-6.688	0.582
prime_age	1.353	1.506	-1.468	4.474
first_round	-0.82	3.925	-8.303	7.075
draft_pick	-0.125	0.1	-0.346	0.044
out.degree	-3.302	2.232	-8.516	0.231
in.degree	2.271	0.977	0.647	4.488
reciprocity	2.215	2.208	-1.563	7.297
transitive.triangles	0.174	0.258	-0.317	0.676

	NBA (30)	WC (15) Western Conference	EC (15) Eastern Conference
Significant	contagion in.degree	contagion in.degree tenure	contagion in.degree player position
Not significant	age/prime_age first round pick out.degree tenure player position (guard)	age/prime_age first round pick out.degree player position (guard)	age/prime_age first round pick out.degree tenure

Actionable Insights & Recommendations

Team tenure may matter

Insight:

While the effect of team tenure on scoring was not statistically conclusive, the direction of the estimate was positive, suggesting a potential link between a player's time on the team and their likelihood of becoming a high scorer. This trend implies that familiarity with the team's system, culture, and playbook may contribute to increased offensive output over time.

Recommendations:

- Invest minutes and development in players who have been with the team longer.
- Stability in player roles and mentorship from veteran teammates may help newer players grow into scoring roles over time.