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Access the code and data at https://github.com/kevbaer/nflpa_24

Representing the Players ABCDEFG*

NFLPA | 2024 Analytics Case Competition
UCLA + Bruin Sports Analytics Entry

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ABSTRACT Space: the final frontier. These are the voyages of the starship *Enterprise*. Its continuing mission: to explore strange new worlds. To seek out new life and new civilizations. To boldly go where no one has gone before!

1 Segmentation of Contracts

NFL contracts are complicated. We are not lawyers. But a contract's salary cap implications are a bit easier to parse. Using a great tool, Arjun Menon and Brad Spielberger's Expected Contract Value Calculator (Menon & Spielberger, 2024), We can see that there are 3 main inputs to all contracts: Years, Total, and % Guaranteed.

*Quarto template from Andrew Heiss https://github.com/andrewheiss/hikmah-academic-quarto.

Justin Madubuike's Contract Info

	TEAM	YEARS	TOTAL	APY	% GTD	CONTRACT TYPE	AGE
		4	$98,000,000	$24,500,000	49.49%	UFA	26

Table: Arjun Menon

Figure 1: Sample Player Contract Details on Expected Contract Value Calculator

APY (Average per Year) is simply just Total divided by Years, so we can quickly get to two variables: How much is the player making per year, and how much money does the player know they are going to make (via guarantees)? Indeed, when reading about extension disputes, they typically focus on these two amounts.

When trying to create compensation tiers, one could just use heuristics, but we prefer a more scientific method of K-Means Clustering. Since we have simplified a players contract down to 2 metrics (APY and Guaranteed), we can algo-organize the contracts into distinct groups. See Section 4 for more details on the computational decisions. Since we'll be comparing players from two different eras (10 years ago vs. Present) and the salary cap has changed greatly, OverTheCap has inflated apy and inflated guaranteed to adjust for this. More on inflating values to match differing salary caps later.

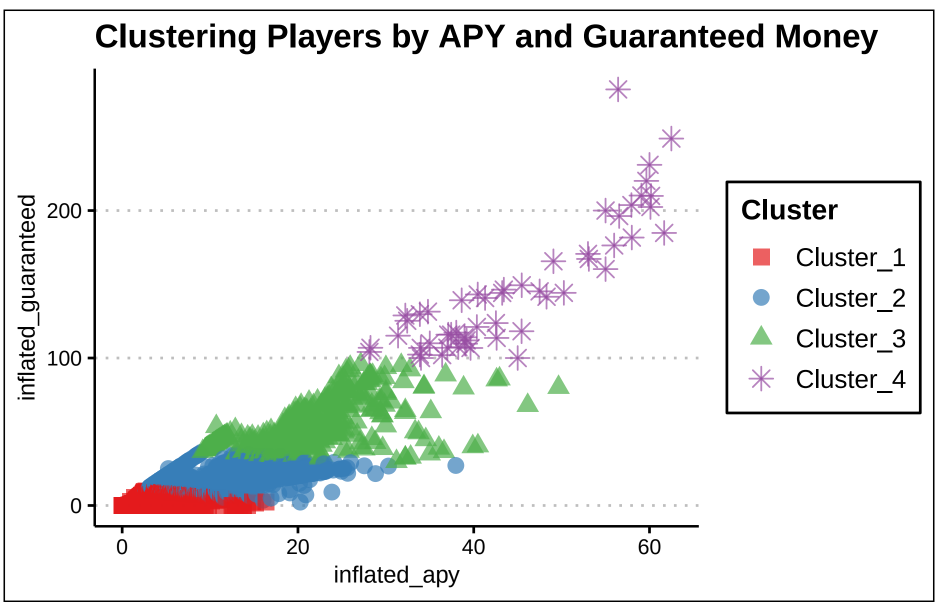

Figure 2: K-Means Clustering

We have four clusters! It's difficult to tell how big each is, but we can clearly tell that there are fairly distinct borders between the four clusters. Let's look more closely at the different clusters.

Breakdown of Clusters

TIME	MEAN_APY	MEAN_GUARANTEED	MEDIAN_APY	MEDIAN_GUARANTEED
Cluster_1				
Current 2022-2024	1.52	0.73	1.12	0.06
Past 2015-2017	1.43	0.54	0.95	0.00
Cluster_2				
Current 2022-2024	9.41	17.00	8.52	15.46
Past 2015-2017	9.64	17.46	8.91	16.06
Cluster_3				
Current 2022-2024	22.10	54.32	22.00	48.29
Past 2015-2017	18.99	49.81	18.35	44.48
Cluster_4				
Current 2022-2024	52.48	179.50	55.00	184.82
Past 2015-2017	35.97	114.51	37.10	109.70

Figure 3: Mean and Median per Cluster

From this table, we can see a lot of interesting things, many that we'll get to later. For now though, it looks like Cluster 1 players make about 1 million dollars per year, Cluster 2 players 10 million, Cluster 3 players 20 million, and Cluster 4 players about 50 million. I think this matches up well with a heuristic approach, but we're also factoring in guaranteed money, as this financial stability is one of the things that differentiates contracts. As the Menon & Spielberger contract value calculator demonstrates, players who have more guaranteed money make a larger percentage of their contracts total value. Teams love to sign players to be APY deals knowing that they'll cut them before they get the large back-end contract value. Nothing wrong with that since all agents and players know this when they sign the contract.

Note that inflated guaranteed is over the whole contract (this helps give weight to those who have longer contracts) and each player is only listed in each era once to prevent Cluster 1 from being over-weighted with players who are cut and signed multiple times per season.

Sample of **Cluster 1** random selection of 10			
year_signed	player	inflated_apy	inflated_guaranteed
2017	Torry McTyer	0.85	0.01
2017	Quinton Patton	1.22	0.04
2017	Bradley Marquez	1.23	0.00
2015	Jake Murphy	0.86	0.00
2015	Jordan Todman	1.36	0.04
2017	Brandon Bell	0.85	0.01
2016	Andre Caldwell	1.46	0.00
2017	Avery Williams	0.85	0.01
2022	J.D. McKissic	4.29	4.47
2016	Erin Henderson	3.29	1.23

Sample of **Cluster 2** random selection of 10			
year_signed	player	inflated_apy	inflated_guaranteed
2015	Cedric Ogbuehi	4.16	15.56
2016	Ronnie Stanley	8.42	33.69
2024	Spencer Brown	18.00	33.40
2017	Stacy McGee	7.65	13.76
2017	Andre Branch	12.23	26.15
2022	Rob Havenstein	14.11	30.27
2015	Dwayne Bowe	11.59	16.04
2023	Jamaal Williams	4.54	9.26
2016	Sean Smith	15.63	32.90
2017	Menelik Watson	9.37	16.82

Figure 4: Cluster 1 and Cluster 2 Sample Contracts

Sample of **Cluster 3** random selection of 10			
year_signed	player	inflated_apy	inflated_guaranteed
2022	Davante Adams	34.35	80.61
2023	Jeffery Simmons	26.70	67.41
2024	Jonathan Greenard	19.00	42.00
2023	Zach Allen	17.33	36.92
2016	Brock Osweiler	29.61	60.86
2022	Brandon Scherff	20.24	36.80
2017	Jamie Collins	19.12	40.37
2016	Jared Goff	11.49	45.95
2015	Julio Jones	25.40	83.78
2023	Dre'Mont Jones	19.51	34.08

Sample of **Cluster 4** random selection of 10			
year_signed	player	inflated_apy	inflated_guaranteed
2015	Ben Roethlisberger	38.95	114.08
2023	Nick Bosa	38.63	139.17
2024	Trevor Lawrence	55.00	200.00
2022	Deshaun Watson	56.43	282.14
2024	Jared Goff	53.00	170.61
2024	Jordan Love	55.00	160.30
2017	Matt Stafford	41.29	140.70
2022	Matt Stafford	49.07	165.61
2015	Russell Wilson	39.04	109.70
2023	Daniel Jones	45.44	118.16

Figure 5: Cluster 3 and Cluster 4 Sample Contracts

What does the breakdown of these clusters look like when comparing the whole NFL from 2015-2017 to 2022-2024?

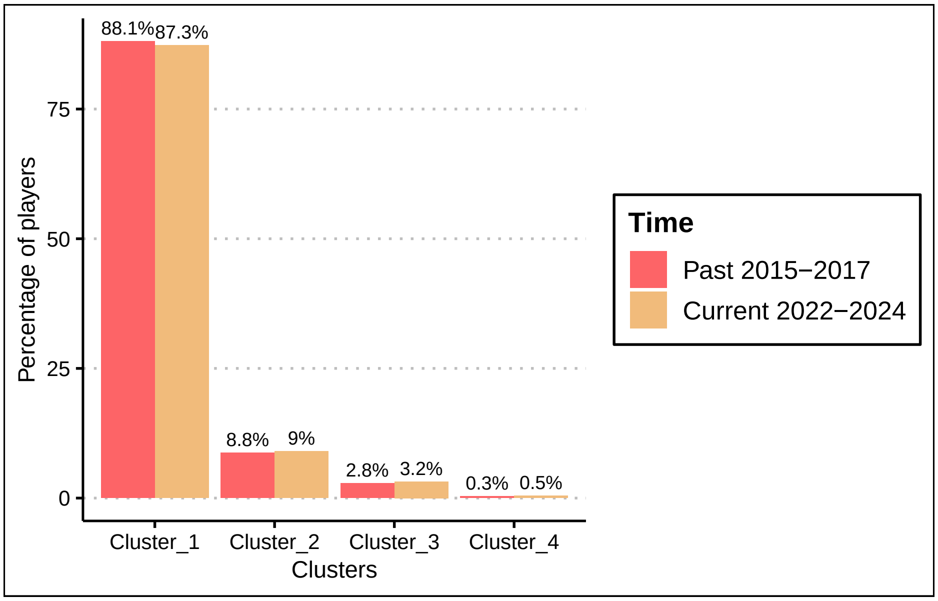

Figure 6: Comparing 2015-2017 to 2022-2024 for each cluster

After this thorough analysis (adjusting for changes in the salary cap, length of contract, guaranteed vs APY, etc.) We have finally reached some sort of analysis of changes in NFL team building strategy, and the take away is... largely the same. The NFL has not changed much. in the past 7-10 years, teams are still relying heavily on min salary players with little to no guaranteed money (median for cluster 1 is 0.06 million dollars guaranteed) with about 10% early draft picks and well paid veterans, and about 4% superstars. It's interesting that clusters 2 to 4 have ticked up slight from 2015-2017, this potentially suggests teams are focusing more on using their salaries for difference makers, letting the leagues relative depth of players (only 1.6% of college players make it to the NFL!)(NFL_Operations, 2024) Since 87% of players signed between 2022-2024 are in Cluster 1, that is our middle class, making on average 1.12 million per year, just above the min salary for rookies of 0.795 million per year, and below the min salary for veterans (4 or more years). This suggests that a large percentage of our middle class players are not veterans, instead players in their first three seasons who were late draft picks or undrafted and are bouncing around rosters looking for a contract that promises financial and familial stability. In the next section, we'll look at our claim that when adjusting for the inflation in the salary cap, the middle class has not changed much and what this means for roster building, and the NFLPA, before finally exploring our suggestions for how the NFLPA can best advocate for these middle class players.

2 How Has the Middle Class Changed?

Over the past 10 years, we found that our four clusters had stayed largely consistent in terms of percent breakdown, with cluster 1 at ~88%, cluster 2 at ~9%, cluster 3 at ~3%, and cluster 4 at ~0.5%. But this does not mean that the salary cap inflation explains everything. For one, the NFL salary cap inflation has far outpaced US dollar inflation, meaning that cluster 1 players are making more now compared to 2015 vs the rest of the population. On the other hand, according to our analysis, the average NFL contract length when signed has gone down from 2.47 in 2015-2017 to 2.42 in 2022-2024. This decrease of 0.05 years per contract might not seem like much, but it means that one out of every twenty contracts is one year shorter than in 2015-2017, all else being equal. This provides a meaningful decrease in financial security – these players can't automatically replace that contract with a new one like a Dak Prescott who took shorter contracts on purpose to maximize his earnings. Furthermore, with a wide variety of NFL incentives being based on how many years you play in the NFL for, contracts being shorter now than in 2015-2017 hurts these middle class players who are seeking that long term security.

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3 References

Arnold, J. B. (2024). *Ggthemes: Extra themes, scales and geoms for 'ggplot2'*. https://CRAN.R-project.org/package=ggthemes

Hvitfeldt, E., & Bodwin, K. (2024). *Tidyclust: A common API to clustering*. https://CRAN.R-project.org/package=tidyclust

Iannone, R., Cheng, J., Schloerke, B., Hughes, E., Lauer, A., Seo, J., Brevoort, K., & Roy, O. (2024). *Gt: Easily create presentation-ready display tables*. https://CRAN.R-project.org/package=gt

Menon, A., & Spielberger, B. (2024). *Expected contract value calculator*. PFF. https://arjunmenon.shinyapps.io/ExpectedContractValue/

Mock, T. (2023). *gtExtras: Extending 'gt' for beautiful HTML tables*. https://CRAN.R-project.org/package=gtExtras

Neuwirth, E. (2022). *RColorBrewer: ColorBrewer palettes*. https://CRAN.R-project.org/package=RColorBrewer

NFL_Operations. (2024). *College advisory committee*.

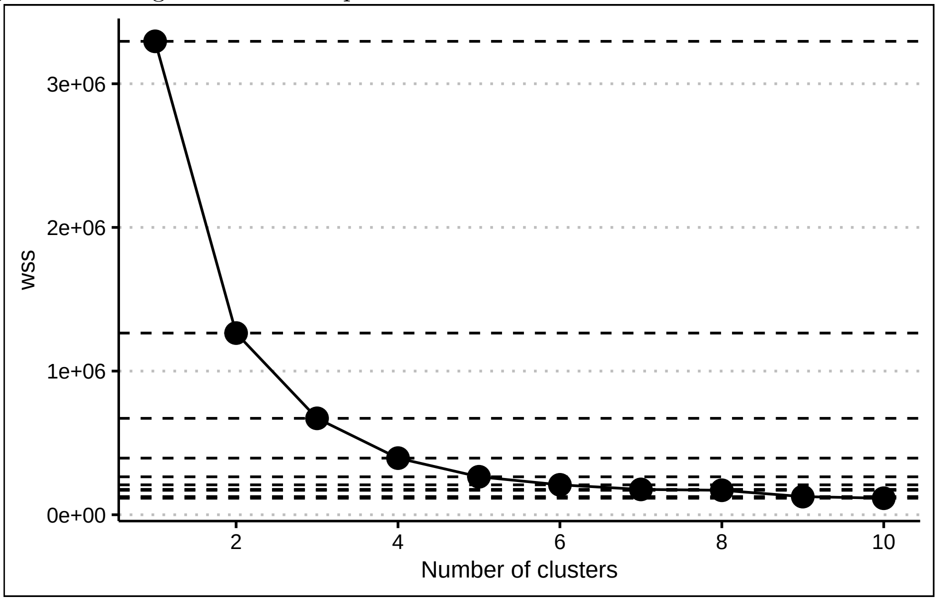
R Core Team. (2024). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Ram, K., & Wickham, H. (2023). *Wesanderson: A wes anderson palette generator*. https://CRAN.R-project.org/package=wesanderson

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., … Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

4 Appendix A (K-means Clustering) :

K-means clustering is a good choice for grouping data points but one key question is how many groups to make. Certain numbers are better choices than others based on the data, and here we use a Scree plot to find the greatest value with significant change from the one prior.



From this we can see that 3 or 4 could both be good choices, but having 4 clusters will give us more specificity and detail which is a benefit.