PLAYER SIMILARITY TOOL FOR RECRUITMENT

PROJECT REPORT

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PROBLEM STATEMENT

We are aiming to build a player similarity model, which can be used by football teams for scouting, talent recruitment and even in transfers. This will mainly help teams to find players with similar traits and characteristics to top players in the world. This will be a really useful tool for teams mainly in lower tier leagues and those who can't afford to bring in top players for their team.

OBJECTIVE

The main objective of this task is to find players with a similar style of play to a particular player from the dataset. The similarity can be calculated for all attributes of the player or certain select attributes provided by the user.

As another objective, we have performed interpolation of players of same/different positions and generated players with the combined features of both the selected players. This is achieved by taking the vector representation of one player, then mixing it with the vector of the second player to get the interpolated vector, and then looking for the closest players from the dataset. This feature is really helpful for teams who want to recruit multi- faceted players and also look for talents in similar areas.

DATASET

Our dataset consists of all the players from the top 5 football leagues (Premier League, La Liga, Bundesliga, Serie A and Ligue 1) and also the Dutch and Indian leagues. It contains the data of around 3500 players. The total number of attributes for each player is 105,

regardless of his position. For example, an attacker may have zeros in goalkeeping attributes, but still those attributes will be present.

We have split the attributes based on whether they are pertaining to one of the three basic divisions : attacking, defence and passing.

OUR APPROACH & METHODOLOGY

Our basic approach to solving this problem was to adapt unsupervised learning. Here we take each player's vector representation according to their attributes. We decided to relate the similar vectors based on cosine similarity rather than the conventional Euclidean distance. The extraction of similar players is performed using K-means clustering.

ELBOW METHOD

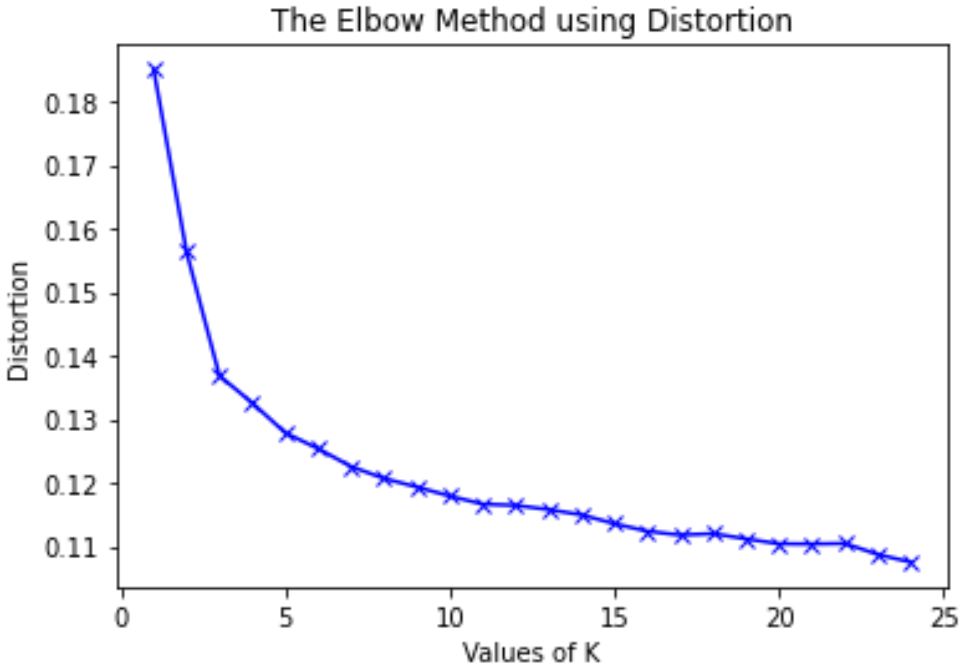
The elbow method is used to determine the number of clusters needed for effective performance of the model. The intuition is that increasing the number of clusters will naturally improve the fit (since there are more parameters to use) but that at some point this can lead to overfitting. The elbow model reflects this. For example, given data that actually consist of k labelled groups, clustering with more than k clusters will "explain" more of the variation (since it can use smaller, tighter clusters), but this is over-fitting, since it is subdividing the labelled groups into multiple clusters. The idea is that the K clusters will add much information, since the data actually consist of that many groups (so these clusters are necessary), but once the number of clusters exceeds the actual number of groups in the data, the added information will drop sharply, because it is just subdividing the actual groups. Assuming this happens, there will be a sharp elbow in the graph of explained variation versus clusters: increasing rapidly

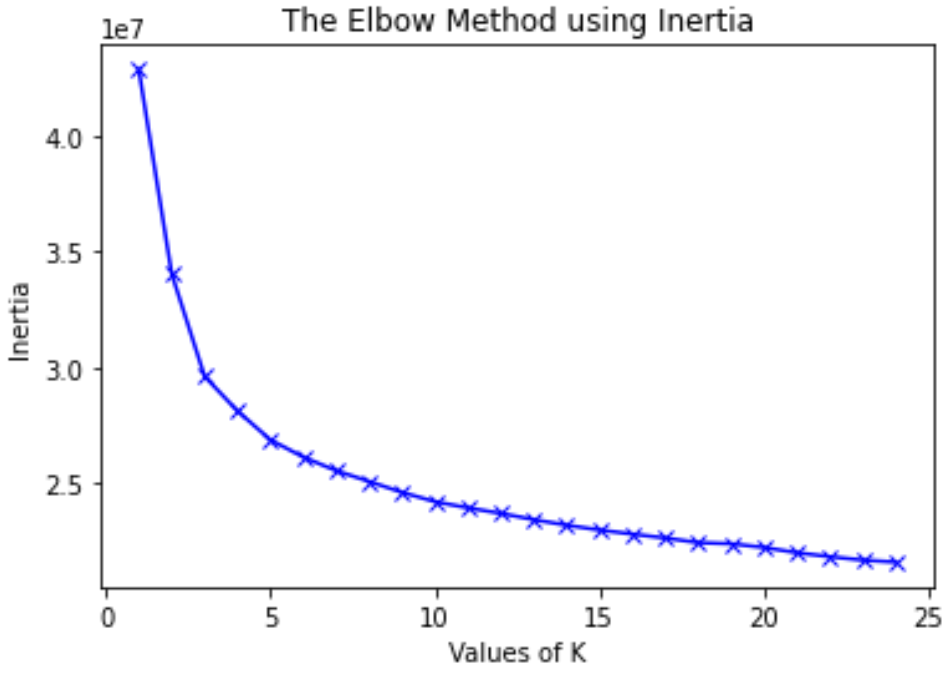
up to k (under-fitting region), and then increasing slowly after k (over-fitting region).

We now define the following: -

DISTORTION (Variance) : It is calculated as the average of the cosine distances from the cluster centers of the respective clusters.

INERTIA : It is the sum of distances of samples to their closest cluster centers.





From the above visualization, we can see that the optimal number of clusters should be around 4-5. But visualizing the data alone cannot always give the right answer.

We iterated the values of k from 1 to 25 and calculate the values of distortions for each value of k and calculate the distortion and inertia for each value of k in the given range.

SIMILARITY SCORES

COSINE SIMILARITY

Cosine similarity measures the similarity between two vectors by calculating the cosine of the angle between the two vectors.

Cosine similarity is one of the most widely used and powerful similarity measures in Data Science. It is used in multiple applications such as finding similar documents in NLP, information retrieval, finding similar sequences to DNA in bioinformatics, detecting plagiarism and many more.

Cosine similarity is calculated as follows :

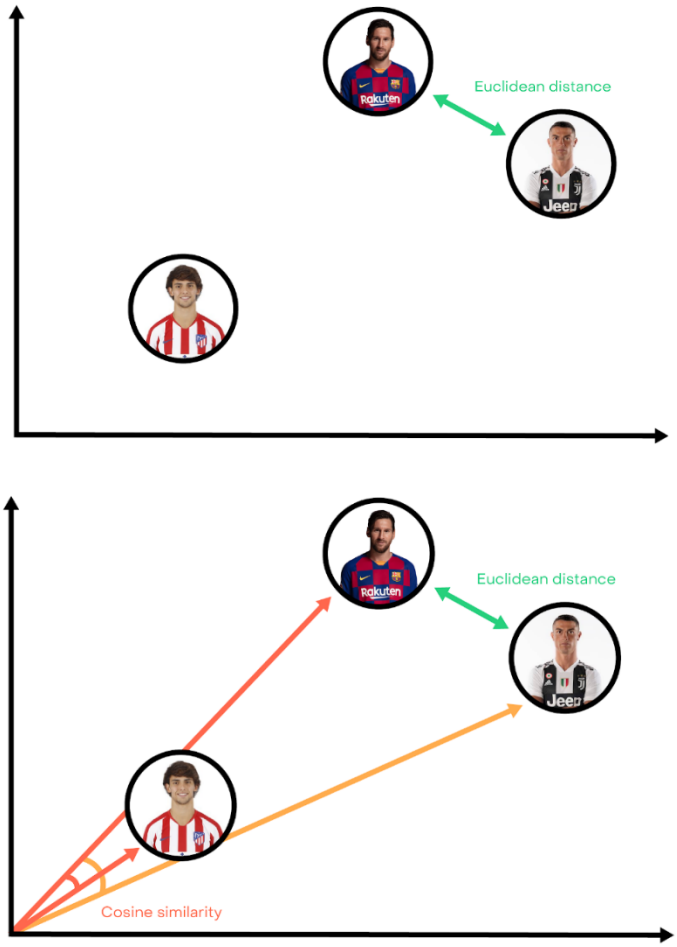
$$cos(\theta) = \frac{x.y}{\|x\| \, \|y\|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}$$

The cosine of 0° is 1, and it is less than 1 for any angle in the interval (0,π] radians.

COSINE vs EUCLIDEAN

Cosine similarity is a measure of similarity between two non-zero vectors in the feature space that measures the cosine of the angle between them. It is thus a judgment of orientation and not magnitude: two vectors with the same orientation have a cosine similarity of 1, two vectors oriented at 90° relative to each other have a similarity of 0, and two vectors diametrically opposed have a similarity of -1, independent of their magnitude.

Cosine similarity allows us to better capture "style" rather than pure "statistics" attributes. Cosine similarity is generally used as a metric for measuring distance when the magnitude of the vectors does not matter.



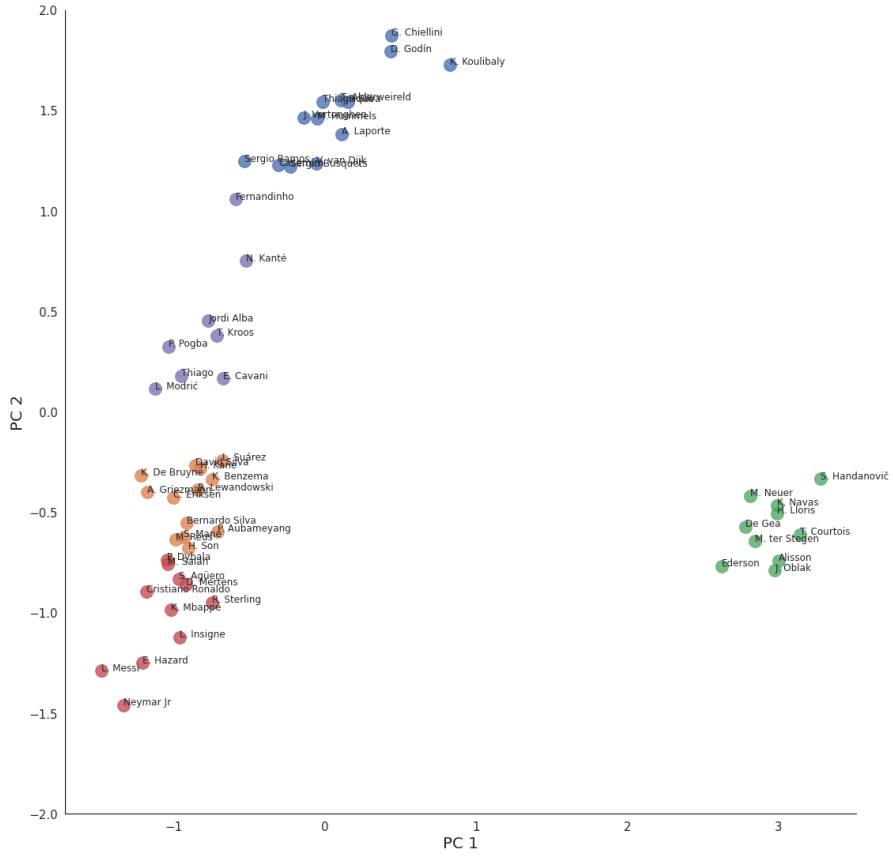
Euclidean distance is like using a ruler to measure the distance. However, choosing this distance is probably not the best option. For

example, Ronaldo is close to Messi because they have high ratings in shoots, speed or dribbles. But a young player like Joao Felix who has the same profile to Messi will be further away because his attributes are weaker, but in the same proportion.

CLUSTERING

Clustering is one of the unsupervised learning techniques (PCA is another one).

We can cluster (or group) observations into the same subgroups so that observations within a subgroup are quite similar to each other and observations in different subgroups are quite different from each other.



K-Means clustering is one of the clustering algorithms.

The basic algorithm :

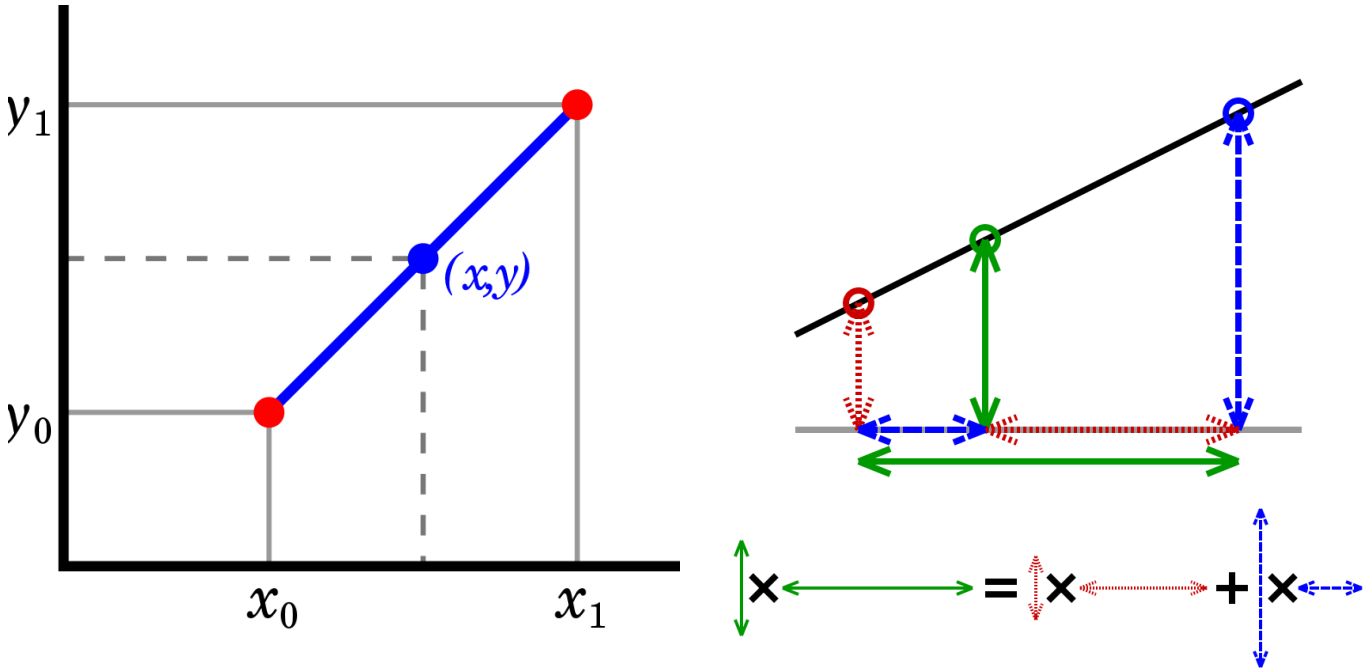
- Specify K-clusters and initialize random centroids

- Iterate until the cluster assignments stop changing. The method assigns each observation to exactly one of the K clusters
- For each K cluster, calculate the cluster mean
- Proceed through the list of observations and assign an observation to the cluster whose mean is nearest.
- The goal is to form the clusters in a way that the observations within the same cluster are as similar as possible.

VECTOR INTERPOLATION

Many a times we come across use cases where the we need to find players with attributes of two or more players, to solve this problem we use vector interpolation. In mathematics, linear interpolation is a method of curve fitting using linear polynomials to construct new data points within the range of a discrete set of known data points. This is the general formula for vector interpolation.

$$v = \alpha.x + (1 - \alpha).y$$



The resultant green vector is a new point which captures both attributes of both the blue and red vectors based on the value of alpha, which is a tuneable parameter.

RESULTS

1. PLAYER SIMILARITY

Chosen player :

Name: Robert Lewandowski
Position: Striker
Nation: Poland
Club: Bayern Munich

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Player_Name: R. Lewandowski
Max_age_players: 37
Market_value_in_euros: 5000000000
No_of_Similar_players: 10
Metrics: All
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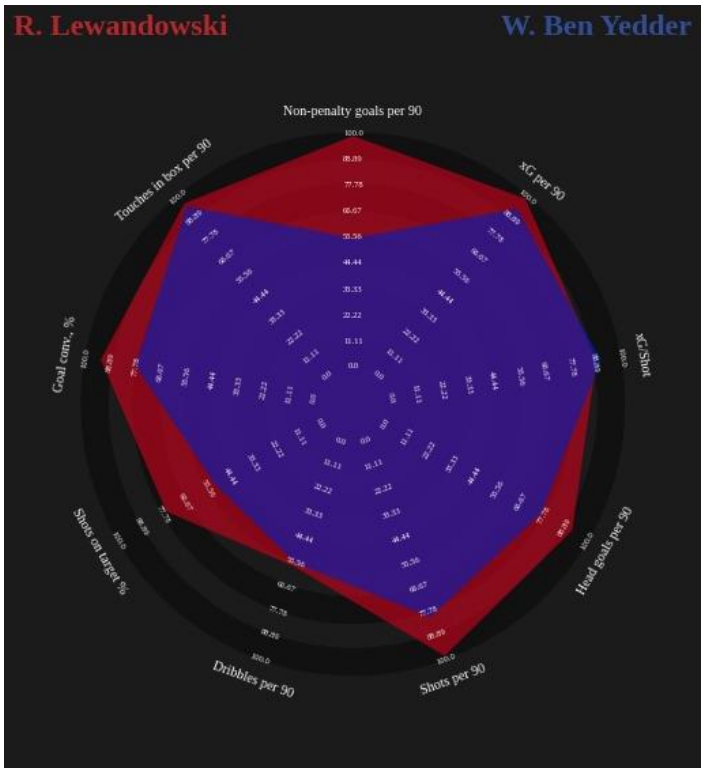
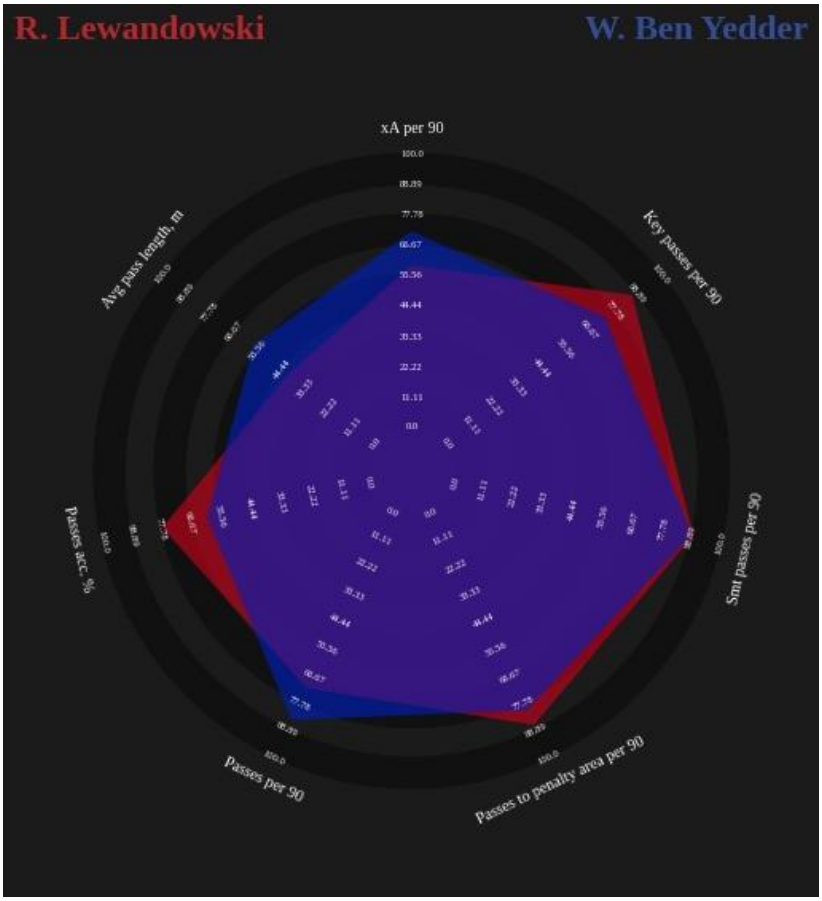
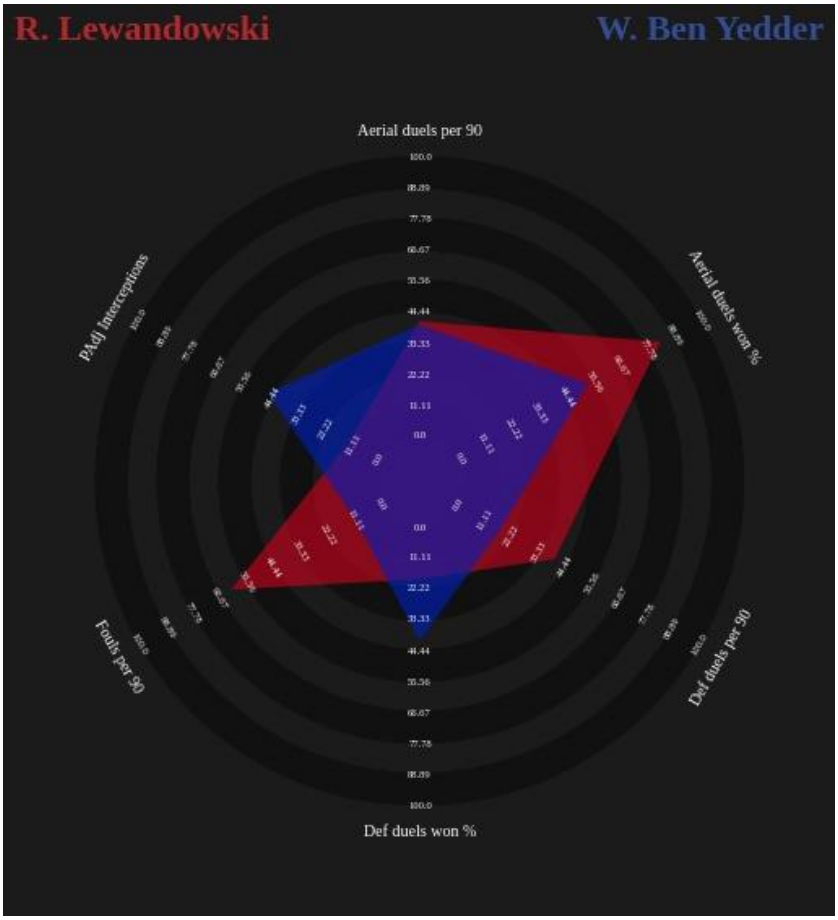
	Player	Team	Categorical position	Position	Age	Market value	Contract expires	cluster	Similarity
1	W. Ben Yedder	Monaco	Centre Forward	CF	30	40000000	2024-06-30	3	96.286630
2	L. Suárez	Atlético Madrid	Centre Forward	CF	34	15000000	2022-06-30	3	95.336272
3	Cristiano Ronaldo	Juventus	Centre Forward	CF, LWF	36	50000000	2022-06-30	3	94.768755
4	K. Benzema	Real Madrid	Centre Forward	CF	33	25000000	2022-06-30	3	94.590932
5	L. Messi	Barcelona	Centre Forward	CF, RWF	33	80000000	2021-06-30	3	94.321295
6	André Silva	Eintracht Frankfurt	Centre Forward	CF	25	37000000	2023-06-30	3	93.457620
7	A. Sánchez	Internazionale	Centre Forward	CF	32	10000000	2023-06-30	3	93.451627
8	H. Kane	Tottenham Hotspur	Centre Forward	CF	27	120000000	2024-06-30	3	93.097973
9	R. Lukaku	Internazionale	Centre Forward	CF	27	90000000	2024-06-30	3	93.015732
10	A. Isak	Real Sociedad	Centre Forward	CF	21	30000000	2024-06-30	3	92.219183




R. Lewandowski
W. Ben Yedder
xA per 90
Key passes per 90
Smt passes per 90
Passes to penalty area per 90
Passes per 90
Passes acc. %
Avg pass length, m


R. Lewandowski
W. Ben Yedder
Aerial duels per 90
Aerial duels won %
Def duels per 90
Def duels won %
Fouls per 90
PAdj interceptions

Attacking Attributes

Player_Name: R. Lewandowski

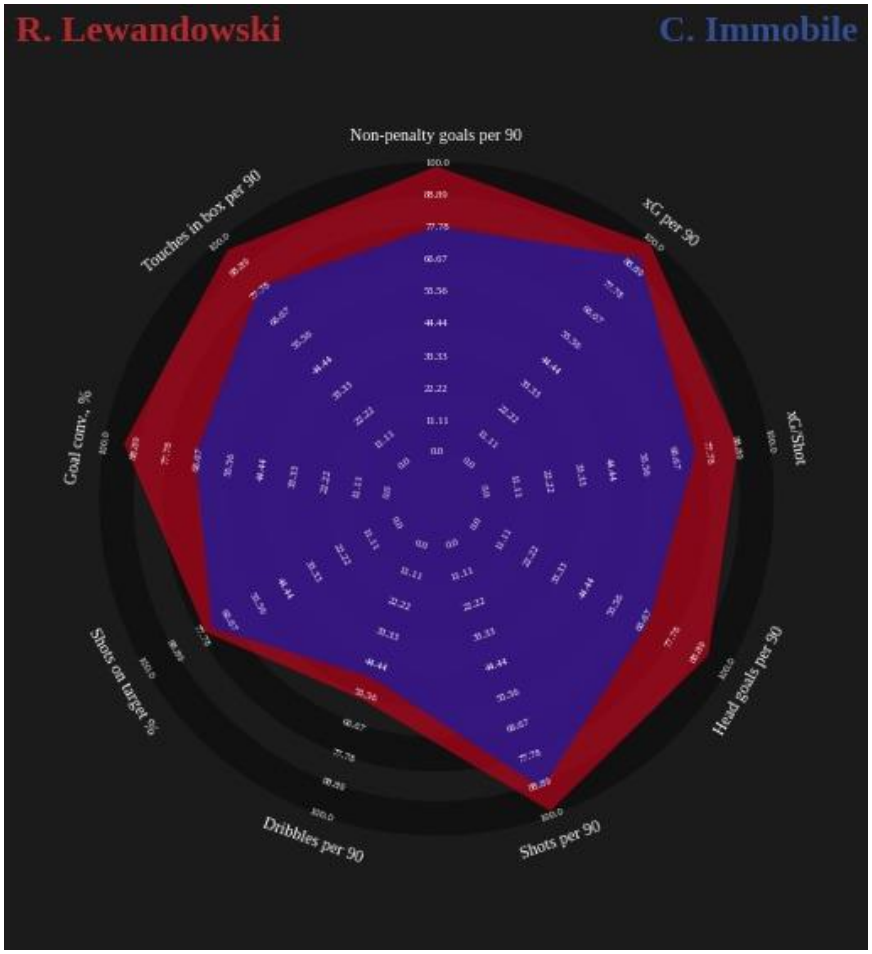
Max_age_players: 37

Market_value_in_euros: 5000000000

No_of_Similar_players: 10

Metrics: Attacking and creativity

	Player	Team	Categorical position	Position	Age	Market value	Contract expires	cluster	Similarity
1	C. Immobile	Lazio	Centre Forward	CF	31	45000000	2025-06-30	1	98.483039
2	André Silva	Eintracht Frankfurt	Centre Forward	CF	25	37000000	2023-06-30	1	98.383262
3	W. Ben Yedder	Monaco	Centre Forward	CF	30	40000000	2024-06-30	1	97.157037
4	L. Suárez	Atlético Madrid	Centre Forward	CF	34	15000000	2022-06-30	1	96.925330
5	K. Benzema	Real Madrid	Centre Forward	CF	33	25000000	2022-06-30	1	96.501725
6	D. Zapata	Atalanta	Centre Forward	CF	29	38000000	2023-06-30	1	96.428132
7	H. Kane	Tottenham Hotspur	Centre Forward	CF	27	120000000	2024-06-30	1	96.107725
8	A. Gouiri	Nice	Centre Forward	CF, LW, LWF	21	20000000	2024-06-30	1	95.542206
9	W. Weghorst	Wolfsburg	Centre Forward	CF	28	30000000	2023-06-30	1	95.541688
10	O. Dorfalou	Vitesse	Centre Forward	CF	27	1000000	2022-06-30	1	95.510332



Passing Attributes

Player_Name: R. Lewandowski

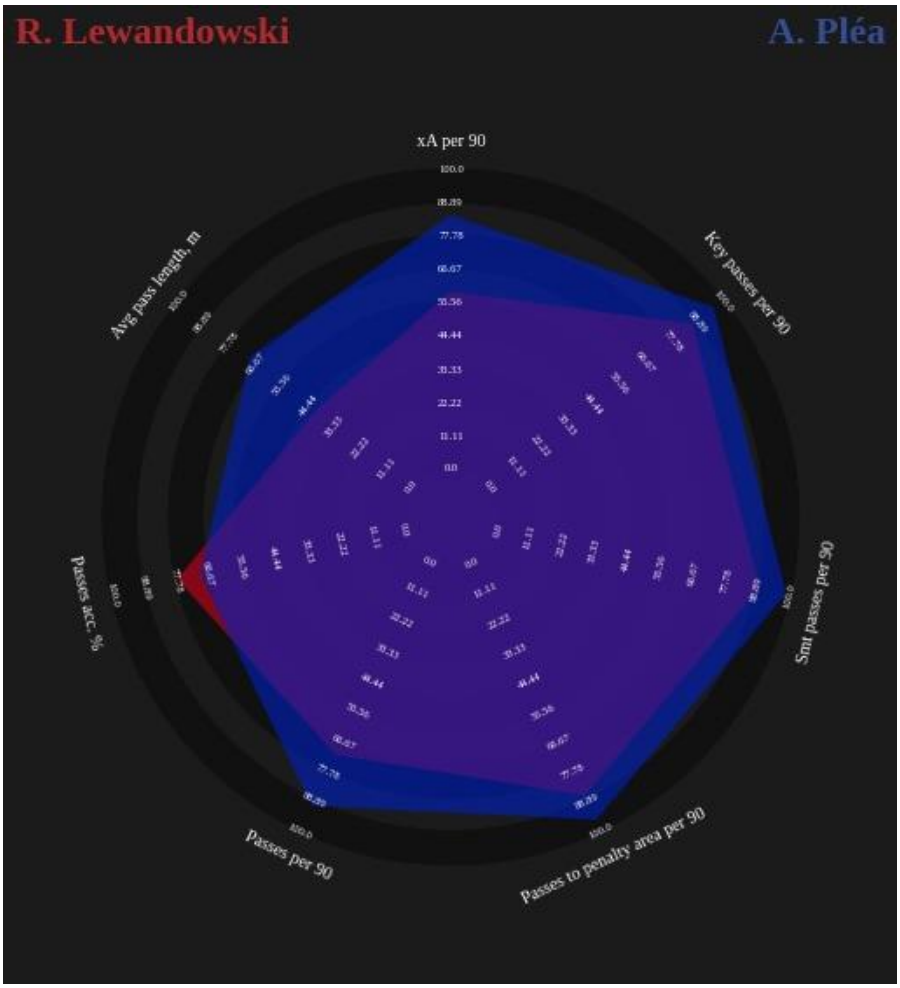
Max_age_players: 37

Market_value_in_euros: 5000000000

No_of_Similar_players: 10

Metrics: Passing and progression

	Player	Team	Categorical position	Position	Age	Market value	Contract expires	cluster	Similarity
1	A. Pléa	Borussia M'gladbach	Centre Forward	CF	28	30000000	2023-06-30	0	97.882132
2	Borja Mayoral	Roma	Centre Forward	CF	23	14000000	2023-06-30	0	97.486017
3	R. Lukaku	Internazionale	Centre Forward	CF	27	90000000	2024-06-30	0	97.101621
4	N. Maupay	Brighton & Hove Albion	Centre Forward	CF, AMF	24	20000000	2023-06-30	0	97.018895
5	W. Ben Yedder	Monaco	Centre Forward	CF	30	40000000	2024-06-30	0	96.802521
6	L. Messi	Barcelona	Centre Forward	CF, RWF	33	80000000	2021-06-30	0	96.499888
7	A. Saint-Maximin	Newcastle United	Centre Forward	CF, LW, RW	24	28000000	2026-06-30	0	96.334973
8	S. Haller	Ajax	Centre Forward	CF	26	30000000	2025-06-30	0	96.159509
9	A. Martial	Manchester United	Centre Forward	CF, LAMF	25	50000000	2024-06-30	0	96.023053
10	K. Benzema	Real Madrid	Centre Forward	CF	33	25000000	2022-06-30	0	95.975815



Defensive Attributes

Player_Name: R. Lewandowski

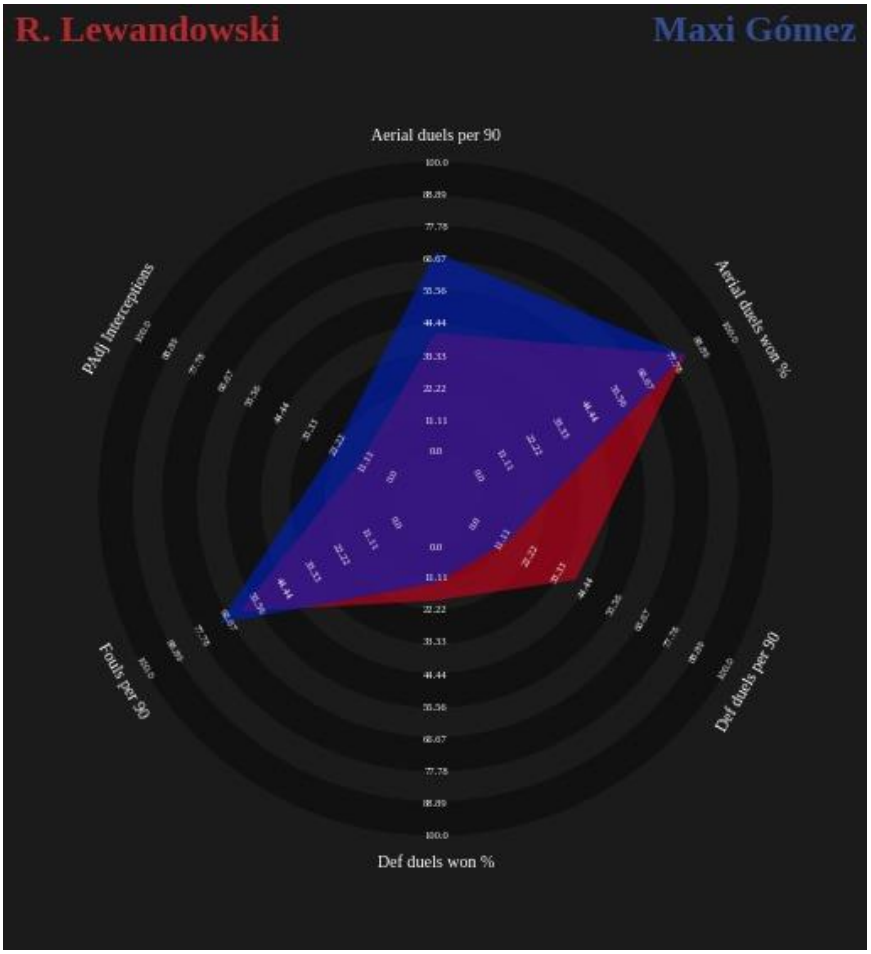
Max_age_players: 37

Market_value_in_euros: 5000000000

No_of_Similar_players: 10

Metrics: Defensive actions

	Player	Team	Categorical position	Position	Age	Market value	Contract expires	cluster	Similarity
1	Maxi Gómez	Valencia	Centre Forward	CF	24	25000000	2024-06-30	2	96.308123
2	L. Messi	Barcelona	Centre Forward	CF, RWF	33	80000000	2021-06-30	2	94.568182
3	K. Opseth	Bengaluru	Centre Forward	CF	31	400000	2022-12-31	2	94.372038
4	B. Yılmaz	Lille	Centre Forward	CF	35	2000000	2022-06-30	2	94.010751
5	A. Isak	Real Sociedad	Centre Forward	CF	21	30000000	2024-06-30	2	93.982964
6	S. Jovetić	Monaco	Centre Forward	CF, LWF	31	6500000	2021-06-30	2	93.083736
7	S. Verdi	Torino	Centre Forward	CF, AMF	28	8000000	2023-06-30	2	93.019051
8	W. Ben Yedder	Monaco	Centre Forward	CF	30	40000000	2024-06-30	2	92.491359
9	A. Delort	Montpellier	Centre Forward	CF	29	15000000	2024-06-30	2	92.411921
10	S. Guirassy	Rennes	Centre Forward	CF	25	13000000	2025-06-30	2	92.082343



2. <u>INTERPOLATION</u>

Chosen Players :	Jordi Alba	Neymar
	Left Back	Forward
	Spain	Brazil
	FC Barcelona	PSG

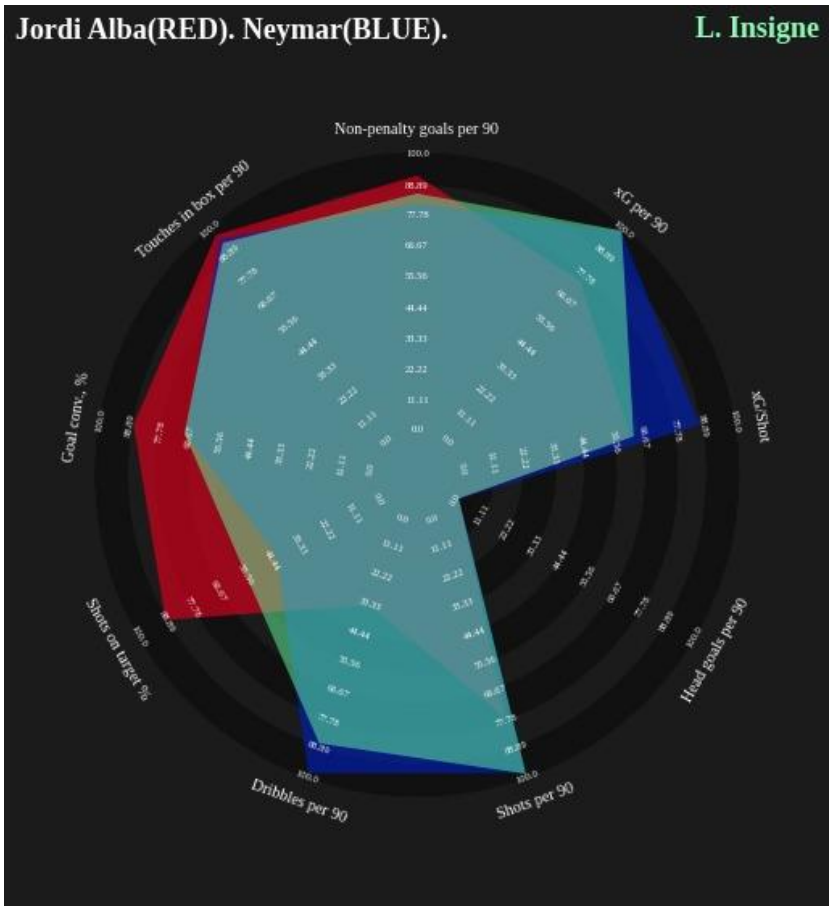
INTERPOLATION FOR PLAYER RECRUITMENT

Player_Name1: Jordi Alba

Player_Name2: Neymar

Percentage_of_player1:

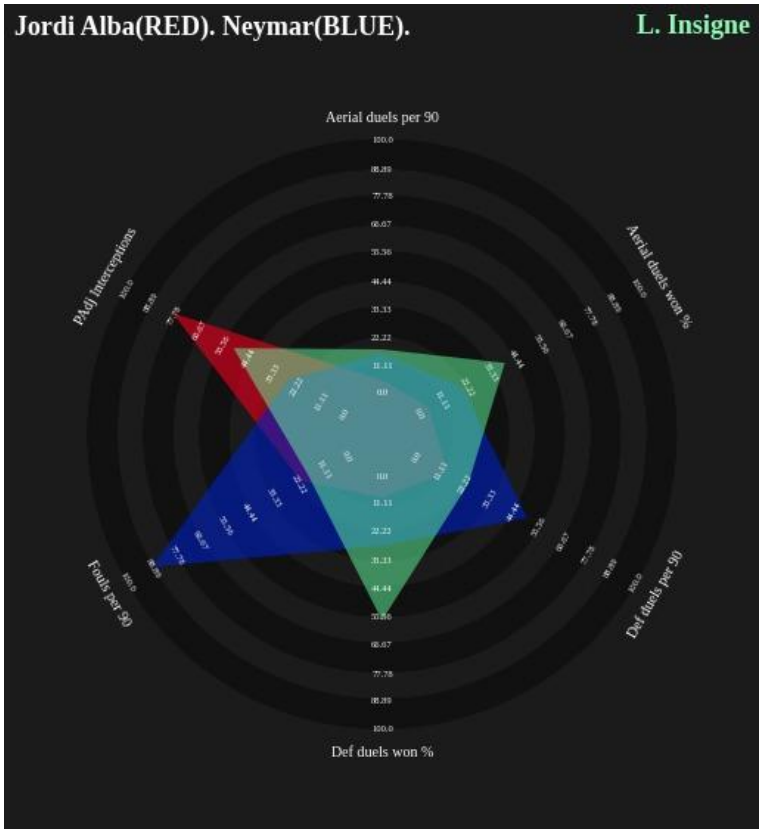
	Player	Team	Categorical position	Position	Age	Market value	Contract expires	Similarity
0	L. Insigne	Napoli	Wingers	LAMF, LWF, LW	29	48000000	2022-06-30	95.965479
1	S. Berghuis	Feyenoord	Wingers	RW, RWF, RAMF	29	12000000	2022-06-30	94.752670
2	D. Tadić	Ajax	Wingers	LAMF, LWF	32	20000000	2023-06-30	94.751127
3	Raphaël Guerreiro	Borussia Dortmund	Full Back	LB, LWB	27	35000000	2023-06-30	93.787052
4	M. Cornet	Olympique Lyonnais	Full Back	LB, LWB	24	12000000	2023-06-30	93.745058
5	D. Berardi	Sassuolo	Wingers	RAMF, RW	26	30000000	2024-06-30	93.690453
6	J. Bamba	Lille	Wingers	LW	24	25000000	2023-06-30	93.623254
7	Marco Asensio	Real Madrid	Wingers	RWF, LWF, RW	25	35000000	2023-06-30	93.419596
8	C. Nkunku	RB Leipzig	Wingers	LAMF, CF, LW	23	33000000	2024-06-30	93.362893
9	A. Januzaj	Real Sociedad	Wingers	RW, RWF, RAMF	26	10000000	2022-06-30	93.308194



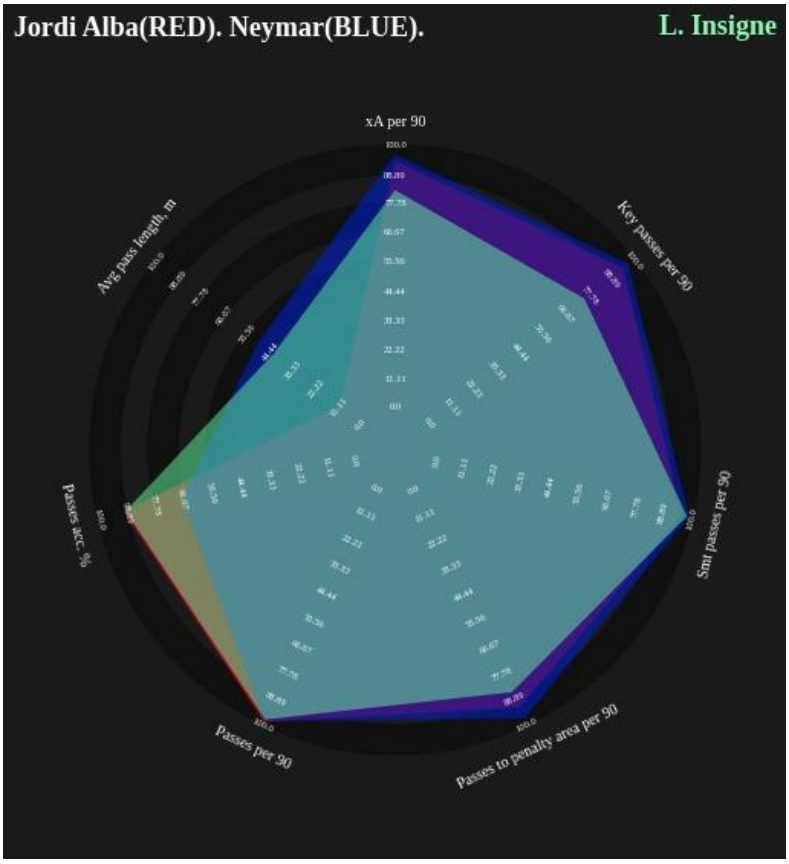
Lorenzo Ingsine (95.9%)

Attacking Attributes

Defensive Attributes

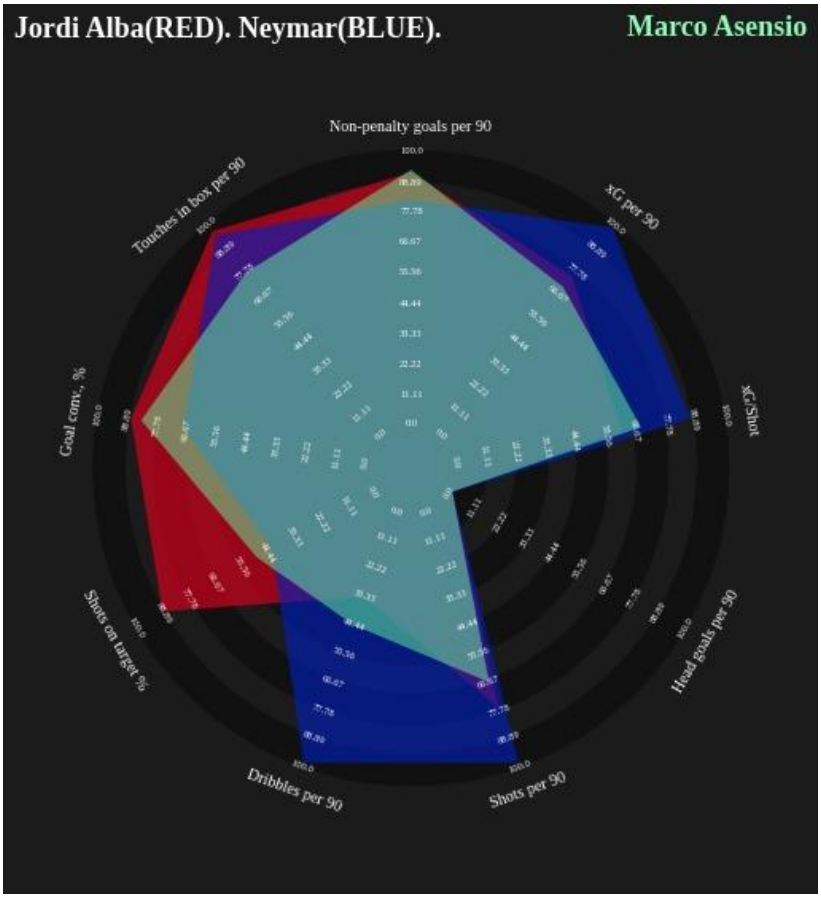


Passing Attributes

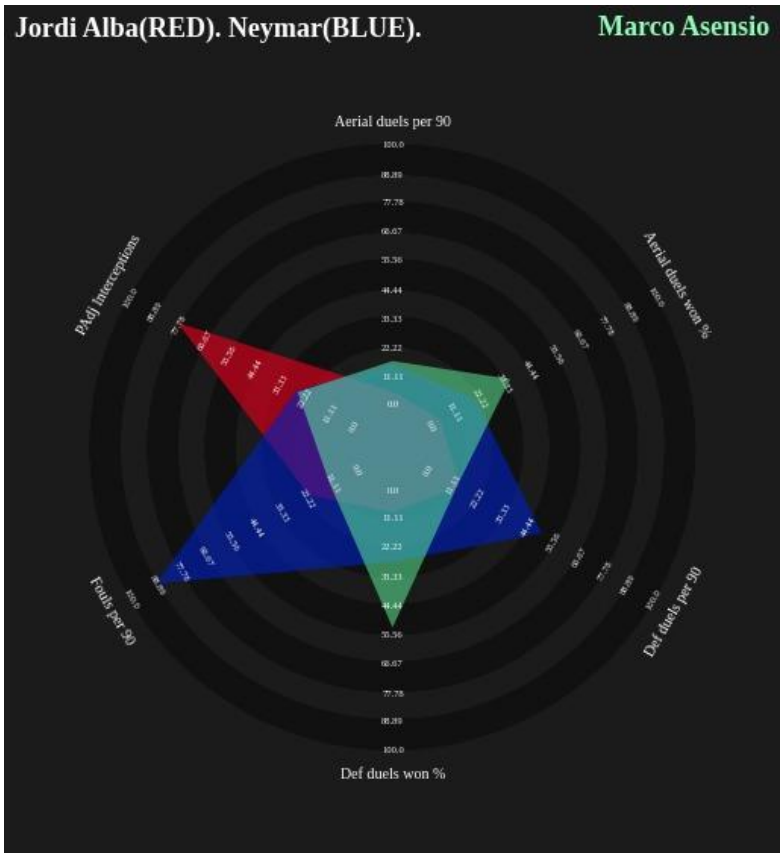


Marco Asensio (93.4%)

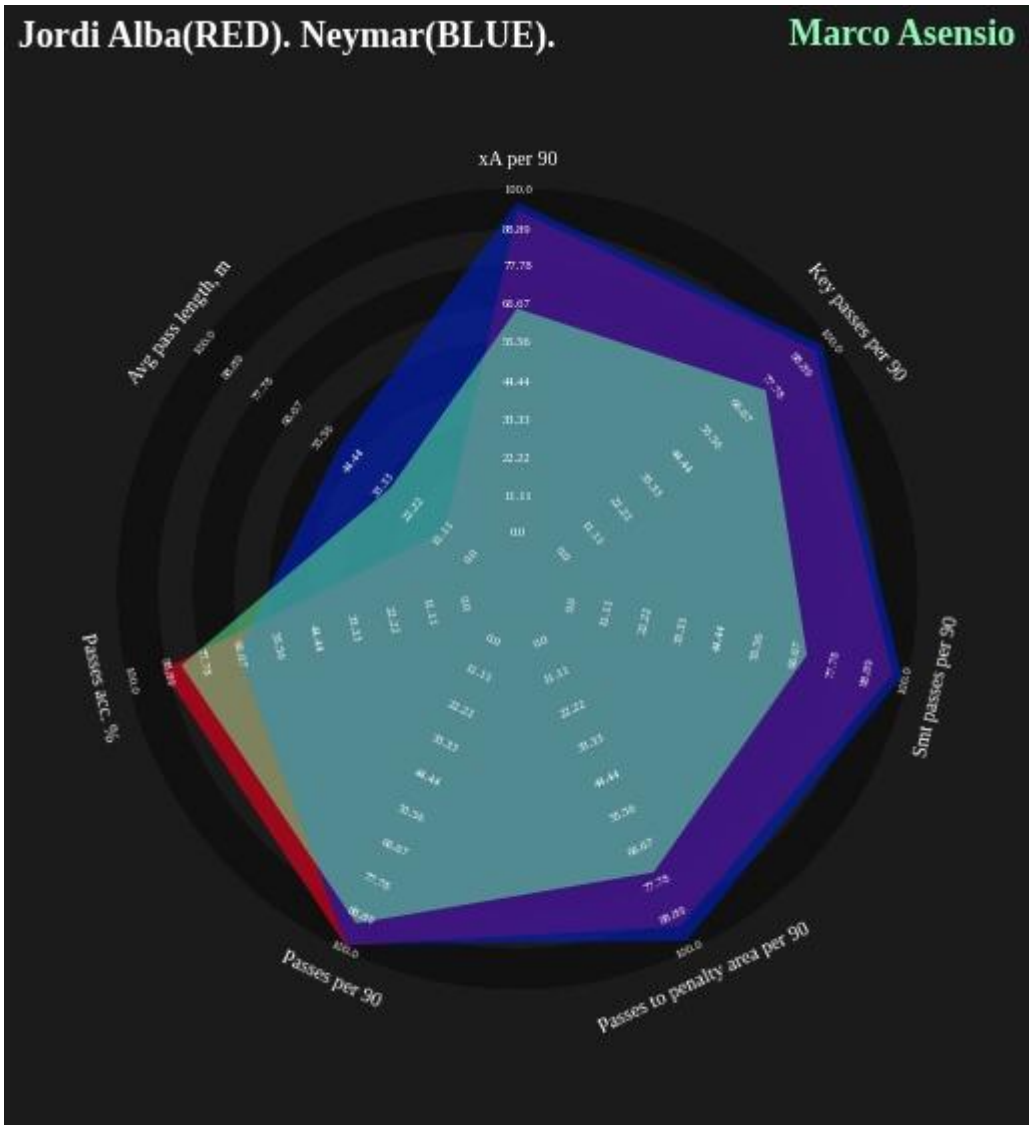
Attacking Attributes



Defensive Attributes



Passing Attributes



OUTCOMES

- We were able to achieve player similarity with more than a rate of 95%
- Both the similarity and interpolation models were tested for different outcomes
- Finding youngsters/ developing players with attributes similar to top players using cosine similarity and K-means clustering was also successful.

FURTHER IMPROVEMENTS / SCOPE :

- The model can be constructed for larger datasets with distributed / parallel programming architectures.
- Further methods of dimensionality reductions methods like PCA, autoencoders etc. can be used.
- To improve dynamic requests, methods of data compression can be employed.
- To improve the run-time performance the model can also be modelled to run with cuda and other GPU frameworks.