PCA/Cluster Analysis/ Regression

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Abstract

This work is part of assignment to find a suitable dataset to perform the PCA a popular dimension reduction technique, perform clustering technique followed by the regression analysis on reduced orthogonal variables and summarize prediction quality.

1 Executive Summary

Our business problem is to look for a suitable dataset for PCA or Factor Analysis techniques. We will apply all the learnt techniques of data exploration and sanitization followed by running the PCA analysis to reduce the dimensions. Perform clustering and then regression techniques to predict some independent variable.

Our key findings are:

- On a high level, our dataset is about the soccer players data and their wages/overall value based on various features like Acceleration, Balance, Agility, dribbling, finishing, diving, kicking and many others.
- We found that 64 variables may be reduced as correlation matrix showed us features very similar to each other. Hence, we applied PCA and observed that dimension reduced from 64 variables to 6 variables which explains the 90% variance of the data.
- Overall principle components were profiled in to 6 components, namely: **Attacker, Defender, PlayerFieldSkills, StrengthAge, Valuation, Athletic.**
- We applied hierarchical clustering technique and found 4 clusters. Their profiles were like PCA grouping. Groups were:
    a. Cluster 1: Attacker
    b. Cluster 2: Valued Players based on Age & Strength
    c. Cluster 3: Valued Athlete based on Age & Strength
    d. Cluster 4: Field Skilled Defender

    This grouping is quite important from business perspective. For example: If there is a business group with some budget in hand and want to form a Soccer team, they could make use of the clusters above to choose players and form a high performing team.

- Our linear regression output showed a stable model with R-square of **0.81** and RMSE of **3.01.**
    a. Although not mandatory, but we ran the 5-fold cross validation to test our modal.

We used the stepwise regression with backward elimination approach to find the best performing model.

2 DATA DESCRIPTION

2.1 DATA SOURCE

Data was collected from Kaggle: https://www.kaggle.com/thec03u5/fifa-18-demo-player-dataset/data which originated from a website in China named: https://sofifa.com/

2.2 DATA SUMMARY

It contained **75 variables** and approx. **17,981 observations**. Approximately half of the columns had values represented as string, though underlying structure of those columns were Continuous. For example: a value of 93 was represented as '90+3'. We sanitized this data and perform arithmetic to this string expression using R and generated the final numerical value.

After filtering out some nominal columns, we considered only **65** variables for analysis. The details of those variables are as below.

Table 1: Variable Description

S. No.	Name	Type	Description	Data Type
1	**Overall**	**Response**	**Overall Point**	**Numerical**
2	Value	Explanatory	Self-Explanatory	Numerical
3	Wage	Explanatory	Self-Explanatory	Numerical
4	Special	Explanatory	Self-Explanatory	Numerical
5	Acceleration	Explanatory	Self-Explanatory	Numerical
6	Aggression	Explanatory	Self-Explanatory	Numerical
7	Agility	Explanatory	Self-Explanatory	Numerical
8	Balance	Explanatory	Self-Explanatory	Numerical
9	Ball.control	Explanatory	Self-Explanatory	Numerical
10	Composure	Explanatory	Self-Explanatory	Numerical
11	Crossing	Explanatory	Self-Explanatory	Numerical
12	Curve	Explanatory	Self-Explanatory	Numerical
13	Dribbling	Explanatory	Self-Explanatory	Numerical
14	Finishing	Explanatory	Self-Explanatory	Numerical
15	Free.kick.accuracy	Explanatory	Self-Explanatory	Numerical
16	GK.diving	Explanatory	Self-Explanatory	Numerical
17	GK.handling	Explanatory	Self-Explanatory	Numerical
18	GK.kicking	Explanatory	Self-Explanatory	Numerical
19	GK.positioning	Explanatory	Self-Explanatory	Numerical
20	GK.reflexes	Explanatory	Self-Explanatory	Numerical
21	Heading.accuracy	Explanatory	Self-Explanatory	Numerical

22	Interceptions	Explanatory	Self-Explanatory	Numerical
23	Jumping	Explanatory	Self-Explanatory	Numerical
24	Long.passing	Explanatory	Self-Explanatory	Numerical
25	Long.shots	Explanatory	Self-Explanatory	Numerical
26	Marking	Explanatory	Self-Explanatory	Numerical
27	Penalties	Explanatory	Self-Explanatory	Numerical
28	Positioning	Explanatory	Self-Explanatory	Numerical
29	Reactions	Explanatory	Self-Explanatory	Numerical
30	Short.passing	Explanatory	Self-Explanatory	Numerical
31	Shot.power	Explanatory	Self-Explanatory	Numerical
32	Sliding.tackle	Explanatory	Self-Explanatory	Numerical
33	Sprint.speed	Explanatory	Self-Explanatory	Numerical
34	Stamina	Explanatory	Self-Explanatory	Numerical
35	Standing.tackle	Explanatory	Self-Explanatory	Numerical
36	Strength	Explanatory	Self-Explanatory	Numerical
37	Vision	Explanatory	Self-Explanatory	Numerical
38	Volleys	Explanatory	Self-Explanatory	Numerical
39	CAM	Explanatory	Center Attacking Midfielder	Numerical
40	CB	Explanatory	Center Back	Numerical
41	CDM	Explanatory	Center Defensive Midfielder	Numerical
42	CF	Explanatory	Center Forward	Numerical
43	CM	Explanatory	Center Midfielder	Numerical
45	LAM	Explanatory	Left Attacking Midfielder	Numerical
46	LB	Explanatory	Left Back	Numerical
47	LCB	Explanatory	Left Center Back	Numerical
48	LCM	Explanatory	Left Center Midfielder	Numerical
49	LDM	Explanatory	Left Defensive Midfielder	Numerical
50	LF	Explanatory	Left Forward	Numerical
51	LM	Explanatory	Left Midfielder	Numerical
52	LS	Explanatory	Left Stricker	Numerical
53	LW	Explanatory	Left Wing	Numerical
54	LWB	Explanatory	Left Wing Back	Numerical
55	RAM	Explanatory	Right Attacking Midfielder	Numerical
56	RB	Explanatory	Right Back	Numerical
57	RCB	Explanatory	Right Center Back	Numerical
58	RCM	Explanatory	Right Center Midfielder	Numerical
59	RDM	Explanatory	Right Defensive Midfielder	Numerical
60	RF	Explanatory	Right Forward	Numerical

61	RM	Explanatory	Right Midfielder	Numerical
62	RS	Explanatory	Right Stricker	Numerical
63	RW	Explanatory	Right Wing	Numerical
64	RWB	Explanatory	Right Wing Back	Numerical
65	ST	Explanatory	Striker	Numerical

2.3 Business Statement

Based on the dataset and combining the assignment objectives, a hypothetical business statement formed is as below:

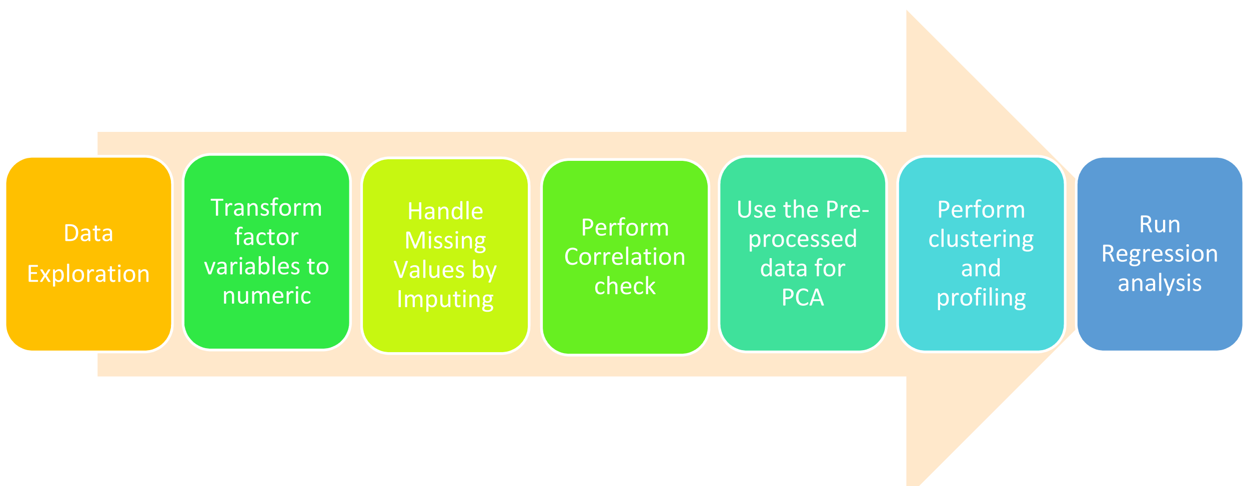
"A new Football franchisee would like to form a team. They have data for approx. 18k players worldwide. Overall, 64 features are available like age, strength, playing style etc. Franchisee would like to define 5-6 features which incorporates all the variables. Also, they would like to apply cluster techniques to create a pool of homogenous player together to form a diverse team.

At the end, they would like to create a regression model which could predict overall points for a new player given the attributes are available."

3 Data Selection and Preprocessing

We followed the following process to analyze the dataset:

Figure 1: Process to Explore the data



3.1 Tools Used

- **R** – Used for Data exploration, imputation using kNN
- **JMP** – PCA, Regression and Clustering
- **Tableau –** For cluster profiling

3.2 DEALING WITH MISSING VALUES

Filling up missing Values in Numerical variables with kNN imputation in R: To proceed further, all the missing values were replaced with imputed values using k-Nearest Neighbour Imputation based on a variation of the Gower Distance for numerical, categorical, ordered and semi-continuous variables. It generates multiple imputations for incomplete multivariate data. A small piece of code has been written in R to implement imputation on numerical data.
Table shown below summarizes the **key statistical indicators** of the attributes that have been imputed. The **Original dataset** and **Imputed dataset** have the almost the **same Mean, Median** and **standard deviation** after imputation:

Table 2: Imputed Dataset

		Original Dataset			*Imputed Dataset*		
S. No.	**Name**	**Rows**	**Mean**	**Median**	**Rows**	**Mean**	**Median**
1	Overall	17980			17980		
2	Value	17980			17980		
3	Wage	17980			17980		
4	Special	17980			17980		
5	Acceleration	17896			17980		
6	Aggression	17912			17980		
7	Agility	17909			17980		
8	Balance	17923			17980		
9	Ball.control	17839			17980		
10	Composure	17886			17980		
11	Crossing	17884			17980		
12	Curve	17907			17980		
13	Dribbling	17849			17980		
14	Finishing	17866			17980		
15	Free.kick.accurac y	17931			17980		
16	GK.diving	17954			17980		
17	GK.handling	17953			17980		
18	GK.kicking	17961			17980		
19	GK.positioning	17954			17980		
20	GK.reflexes	17951			17980		
21	Heading.accuracy	17905			17980		
22	Interceptions	17880			17980		
23	Jumping	17910			17980		
24	Long.passing	17859			17980		
25	Long.shots	17897			17980		
26	Marking	17868			17980		

27	Penalties	17950	17980
28	Positioning	17885	17980
29	Reactions	17865	17980
30	Short.passing	17831	17980
31	Shot.power	17907	17980
32	Sliding.tackle	17885	17980
33	Sprint.speed	17866	17980
34	Stamina	17872	17980
35	Standing.tackle	17856	17980
36	Strength	17876	17980
37	Vision	17873	17980
38	Volleys	17939	17980
39	CAM	15951	17980
40	CB	15951	17980
41	CDM	15951	17980
42	CF	15951	17980
43	CM	15951	17980
44	ID	15951	17980
45	LAM	15951	17980
46	LB	15951	17980
47	LCB	15951	17980
48	LCM	15951	17980
49	LDM	15951	17980
50	LF	15951	17980
51	LM	15951	17980
52	LS	15951	17980
53	LW	15951	17980
54	LWB	15951	17980
55	RAM	15951	17980
56	RB	15951	17980
57	RCB	15951	17980
58	RCM	15951	17980
59	RDM	15951	17980
60	RF	15951	17980
61	RM	15951	17980
62	RS	15951	17980
63	RW	15951	17980
64	RWB	15951	17980
65	ST	15951	17980

3.2 Correlation Check Of Numerical Values

The second step is to analyze the **multi-collinearity effects** in between the numerical variables. Data analysis tool in Excel has been used to compute the correlation matrix using **Pearson's coefficient** and for better interpretation, the results have been compiled in a correlation chart. Please find below the correlation matrix among all numeric variables:

Correlation_Output.xlsx

Table 3: Correlation Matrix

	Value	*Wage*	*Special*	*Acceleration*	*Aggression*	*Agility*	*Balance*	*Ball.control*
Value	1.00	0.85	0.38	0.18	0.19	0.20	0.11	0.31
Wage	0.85	1.00	0.37	0.15	0.21	0.17	0.09	0.29
Special	0.38	0.37	1.00	0.65	0.67	0.69	0.58	0.91
Acceleration	0.18	0.15	0.65	1.00	0.25	0.80	0.70	0.67
Aggression	0.19	0.21	0.67	0.25	1.00	0.24	0.18	0.54
Agility	0.20	0.17	0.69	0.80	0.24	1.00	0.77	0.70
Balance	0.11	0.09	0.58	0.70	0.18	0.77	1.00	0.60
Ball.control	0.31	0.29	0.91	0.67	0.54	0.70	0.60	1.00
Composure	0.40	0.39	0.80	0.44	0.58	0.49	0.37	0.76
Crossing	0.25	0.24	0.86	0.66	0.47	0.69	0.62	0.84
Curve	0.29	0.27	0.85	0.60	0.39	0.68	0.58	0.83
Dribbling	0.27	0.25	0.86	0.74	0.42	0.76	0.66	0.93
Finishing	0.26	0.23	0.71	0.60	0.23	0.63	0.51	0.79
Free.kick.accuracy	0.27	0.25	0.81	0.49	0.40	0.58	0.51	0.77
GK.diving	-0.03	-0.04	-0.67	-0.59	-0.57	-0.52	-0.50	-0.78
GK.handling	-0.03	-0.03	-0.67	-0.59	-0.57	-0.52	-0.51	-0.78
GK.kicking	-0.03	-0.04	-0.67	-0.58	-0.57	-0.52	-0.50	-0.78
GK.positioning	-0.03	-0.04	-0.67	-0.58	-0.56	-0.52	-0.50	-0.78
GK.reflexes	-0.03	-0.04	-0.67	-0.58	-0.57	-0.52	-0.50	-0.78
Heading.accuracy	0.19	0.21	0.65	0.33	0.69	0.26	0.17	0.65
Interceptions	0.14	0.16	0.57	0.15	0.74	0.13	0.15	0.40
Jumping	0.14	0.15	0.31	0.21	0.36	0.21	0.18	0.18
Long.passing	0.30	0.29	0.85	0.43	0.58	0.52	0.46	0.78
Long.shots	0.28	0.26	0.83	0.57	0.39	0.64	0.52	0.83
Marking	0.08	0.11	0.51	0.14	0.72	0.09	0.12	0.36
Penalties	0.24	0.24	0.73	0.53	0.33	0.56	0.48	0.77

Positioning	0.26	0.24	0.81	0.67	0.38	0.70	0.59	0.86
Reactions	0.53	0.50	0.59	0.19	0.40	0.28	0.14	0.43
Short.passing	0.32	0.31	0.90	0.56	0.60	0.61	0.54	0.91
Shot.power	0.28	0.27	0.83	0.54	0.49	0.57	0.45	0.83
Sliding.tackle	0.08	0.12	0.51	0.16	0.71	0.11	0.15	0.37
Sprint.speed	0.18	0.15	0.65	0.92	0.28	0.75	0.64	0.66
Stamina	0.21	0.20	0.79	0.61	0.64	0.56	0.47	0.72
Standing.tackle	0.10	0.13	0.54	0.15	0.73	0.11	0.14	0.40
Strength	0.14	0.17	0.19	-0.16	0.46	-0.24	-0.40	0.08
Vision	0.35	0.32	0.75	0.46	0.30	0.59	0.49	0.72
Volleys	0.29	0.27	0.76	0.57	0.32	0.62	0.51	0.79
CAM	0.45	0.41	0.73	0.49	0.18	0.63	0.48	0.69
CB	0.19	0.22	0.13	-0.32	0.44	-0.30	-0.31	-0.15
CDM	0.31	0.32	0.34	-0.17	0.46	-0.08	-0.12	0.07
CF	0.44	0.40	0.75	0.55	0.20	0.65	0.50	0.73
CM	0.49	0.46	0.75	0.31	0.35	0.47	0.34	0.61
ID	-0.14	-0.21	-0.23	0.12	-0.23	-0.02	0.05	-0.11
LAM	0.44	0.41	0.77	0.53	0.22	0.66	0.51	0.73
LB	0.29	0.30	0.37	-0.03	0.45	-0.01	-0.03	0.08
LCB	0.19	0.22	0.13	-0.31	0.45	-0.30	-0.30	-0.14
LCM	0.48	0.46	0.77	0.33	0.37	0.48	0.36	0.63
LDM	0.31	0.32	0.37	-0.14	0.48	-0.06	-0.10	0.10
LF	0.43	0.40	0.78	0.58	0.23	0.67	0.52	0.76
LM	0.44	0.40	0.80	0.61	0.25	0.70	0.55	0.75
LS	0.44	0.41	0.79	0.54	0.29	0.61	0.43	0.76
LW	0.41	0.38	0.79	0.64	0.22	0.73	0.58	0.78
LWB	0.35	0.35	0.52	0.10	0.48	0.15	0.10	0.24
RAM	0.44	0.40	0.80	0.56	0.25	0.68	0.53	0.77
RB	0.29	0.30	0.39	-0.01	0.47	0.01	-0.02	0.11
RCB	0.19	0.22	0.14	-0.31	0.46	-0.29	-0.30	-0.14
RCM	0.48	0.46	0.79	0.35	0.39	0.50	0.38	0.66
RDM	0.31	0.32	0.38	-0.13	0.49	-0.05	-0.09	0.11
RF	0.43	0.39	0.80	0.60	0.25	0.69	0.53	0.78
RM	0.43	0.40	0.82	0.63	0.27	0.71	0.57	0.77
RS	0.43	0.41	0.80	0.55	0.30	0.62	0.44	0.77
RW	0.41	0.37	0.81	0.65	0.24	0.74	0.59	0.79
RWB	0.35	0.35	0.53	0.12	0.49	0.16	0.11	0.26
ST	0.43	0.41	0.80	0.56	0.30	0.62	0.44	0.78

The results of **correlation matrix** show that **most of the variables are correlated with each other**. That is why out of 65 variables, less than 10 variables explain more than 90% of variance.

4 Dimension Reduction Using PCA

Jmp was used to perform PCA. After the data was processed and run for the dimension reduction. Scree plot was generated as below in Figure (2). Based on this, **6 factors appear** good to be extracted.

Figure 2: Scree Plot

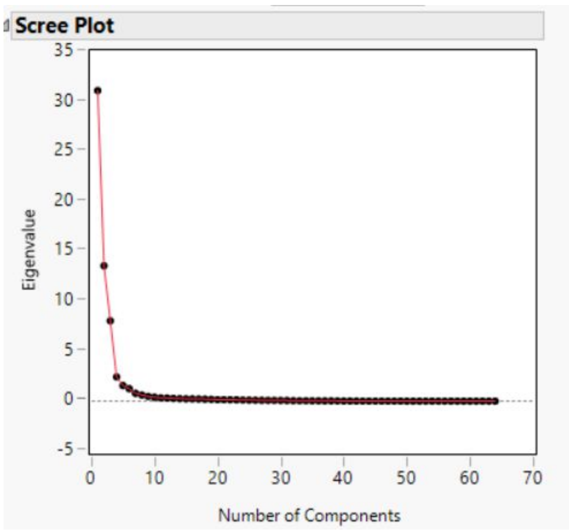
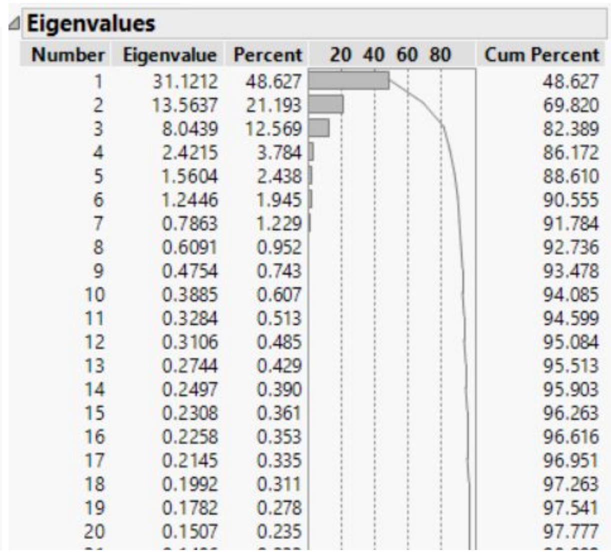


Figure 3: Eigenvalues Cum Percent



Eigenvalues

Number	Eigenvalue	Percent	20 40 60 80	Cum Percent
1	31.1212	48.627		48.627
2	13.5637	21.193		69.820
3	8.0439	12.569		82.389
4	2.4215	3.784		86.172
5	1.5604	2.438		88.610
6	1.2446	1.945		90.555
7	0.7863	1.229		91.784
8	0.6091	0.952		92.736
9	0.4754	0.743		93.478
10	0.3885	0.607		94.085
11	0.3284	0.513		94.599
12	0.3106	0.485		95.084
13	0.2744	0.429		95.513
14	0.2497	0.390		95.903
15	0.2308	0.361		96.263
16	0.2258	0.353		96.616
17	0.2145	0.335		96.951
18	0.1992	0.311		97.263
19	0.1782	0.278		97.541
20	0.1507	0.235		97.777

Furthermore, the cumulative variance was observed using Eignvalues table shown in Figure (3) above. **90%** of the variance is explained by these variables.

Upon analyzing the Varimax Rotated factor loading as shown in Figure (4) below, we extracted following profiles:

Table (4): Profiling based on Principal Components

	Profiles
1	Attacker
2	Defender
3	PlayerFieldSkills
4	StrengthAge
5	Valuation
6	Athletic

Figure 4: Rotated Factor Loading

Factor Analysis: Principal Component / Varimax

Rotated Factor Loading

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Interceptions	-0.033587	0.748945	0.605744	0.026142	-0.009557	0.013220
Value	0.374333	0.215941	-0.009094	0.006753	0.849400	0.029512
Special	0.727763	0.314198	0.582219	0.004179	0.038301	0.143191
CM	0.854610	0.487288	-0.014228	0.001090	0.076486	-0.079586
LCM	0.857766	0.482841	0.011558	-0.000684	0.075763	-0.075982
RCM	0.860992	0.475526	0.049422	-0.003353	0.074729	-0.070367
Marking	-0.129141	0.718941	0.645888	-0.004206	-0.024779	0.005235
Free.kick.accuracy	0.712581	0.058255	0.458607	-0.011226	-0.044840	-0.147027
Positioning	0.776893	-0.176080	0.501333	-0.012727	0.017496	0.096235
Standing.tackle	-0.096947	0.714243	0.664993	-0.017841	-0.006697	-0.017624
CF	0.985475	0.001259	0.048631	-0.020960	0.088963	0.063128
LF	0.982948	-0.001280	0.098125	-0.023822	0.086478	0.070586
RF	0.978784	-0.004104	0.134653	-0.025292	0.084613	0.074436
LB	0.094085	0.982623	-0.040950	-0.028407	0.050925	0.075105
RB	0.102785	0.982626	-0.010314	-0.030195	0.050692	0.078635
Stamina	0.389061	0.251882	0.665203	-0.043035	0.006817	0.307631
Short.passing	0.646097	0.233479	0.640371	-0.049146	0.051956	-0.068698
Ball.control	0.697776	0.040841	0.659842	-0.054351	0.061990	0.038759
Vision	0.843949	0.096058	0.221782	-0.055729	0.009811	-0.144541
Sliding.tackle	-0.126479	0.716957	0.649337	-0.058657	-0.016643	-0.005041
CAM	0.982688	0.100427	-0.021941	-0.070387	0.076575	-0.002852
LAM	0.983881	0.094854	0.044276	-0.073948	0.071195	0.008425
RAM	0.981125	0.089042	0.094040	-0.075917	0.069816	0.014050
Long.passing	0.587420	0.397699	0.544796	-0.076124	-0.001095	-0.181685
Curve	0.762855	0.015070	0.476268	-0.083102	-0.018766	-0.054715
LWB	0.279317	0.944809	0.007262	-0.084180	0.044346	0.073006
RWB	0.283999	0.942779	0.025236	-0.085169	0.044487	0.075144
LW	0.969671	0.022572	0.123178	-0.137297	0.057980	0.093668
RW	0.966210	0.020400	0.148069	-0.137403	0.057233	0.096090
RM	0.957976	0.137390	0.120409	-0.150711	0.060427	0.085576
LM	0.961009	0.142138	0.084550	-0.150926	0.061463	0.082245
Dribbling	0.735276	-0.073942	0.591515	-0.174563	0.026252	0.066674
Crossing	0.669686	0.169459	0.549146	-0.225329	-0.055467	0.017855
Sprint.speed	0.472910	-0.111875	0.457528	-0.379114	0.041041	0.497436
Agility	0.634802	-0.074823	0.345436	-0.420298	-0.048791	0.334040
Acceleration	0.499240	-0.123031	0.439575	-0.446565	0.020246	0.464234
Balance	0.482351	-0.074972	0.363575	-0.547719	-0.106463	0.233510

5 CLUSTERS

We used the Hierarchical clustering technique on the reduced dimensions identified in section (4) above. Upon analyzing the Dendogram diagram, we found that 4 clusters were found to be suitable for the dataset. We then pushed that data to **Tableau** to map those clusters to the different principal components we identified. Figure (5) and (6) shows the dendogram and clusters extracted. The cluster extraction method helps define the franchisee a pool of players based on different skills. They could further analyze the clusters to choose the player.

Figure (5): Dendogram

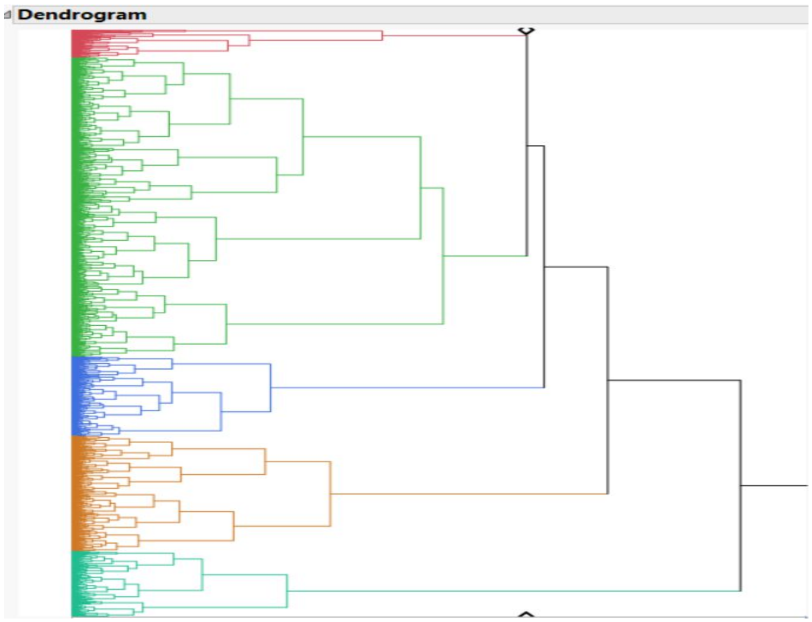
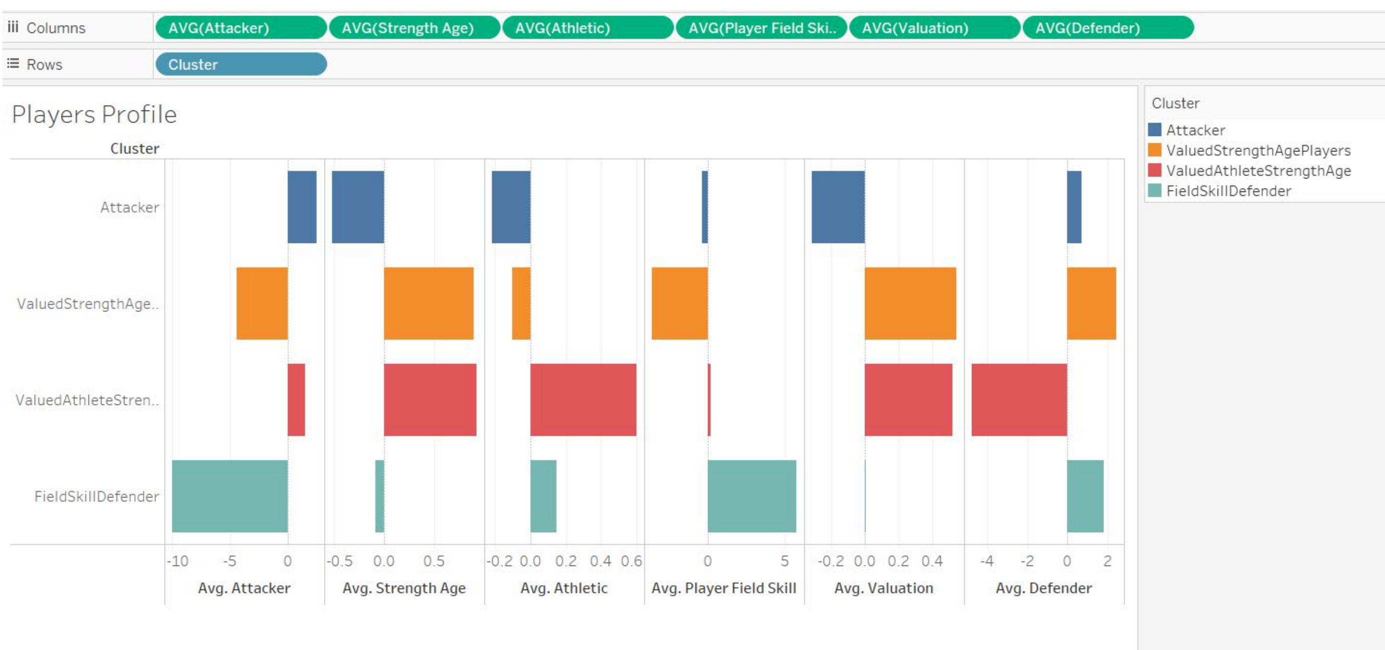


Figure (6): Clusters Vs Principal components



6 REGRESSION MODEL ANALYSIS

Before running the regression model, we checked for major assumptions for a linear regression model:

- Scatter-plot analysis showed little linear relation between dependent variables with independent variable as shown in Figure (7) below.
- Outlier presence was not detected
- Histogram showed that variables to be multivariate normal as shown in Figure (8) below.
- Residual scatter plot found to be homoscedastic as shown in Figure (9) below.

Figure (7): Scatter-plot Y v/s X's

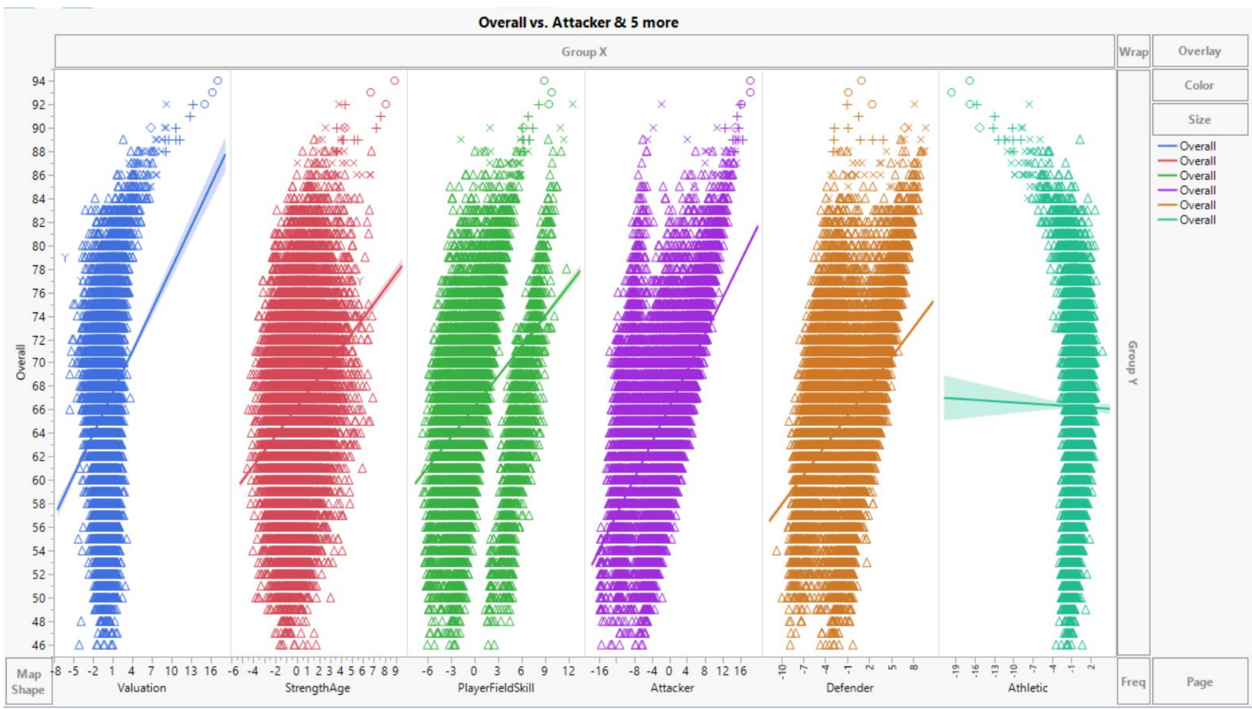


Figure (8): Normal distribution for Multivariate

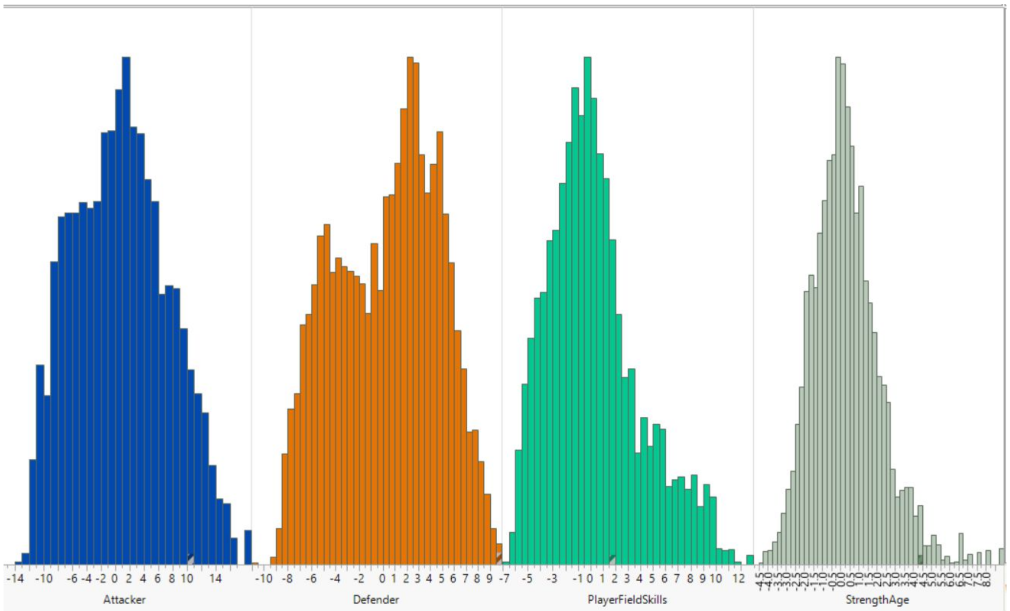
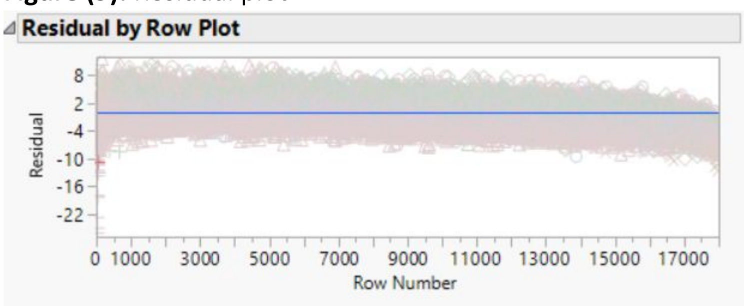


Figure (9): Residual plot



6.1 Model Fit & Parameter Estimates

Figure (10) below shows the summary of fit and parameter estimates. Using the stepwise regression and 5-fold cross validation, we created and validated the model. Overall, though R2 is showing a stable model prediction but overall Prediction error is high. This is expected as the data was little linear with the response variables.

Figure (10): Summary of Fit

Summary of Fit

RSquare	0.81441
RSquare Adj	0.814359
Root Mean Square Error	3.010843
Mean of Response	66.24798
Observations (or Sum Wgts)	17981

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	715046.69	143009	15775.68
Error	17975	162946.55	9.065176	**Prob > F**
C. Total	17980	877993.24		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	66.247984	0.022453	2950.5	<.0001*
Attacker	0.767238	0.004025	190.62	<.0001*
Defender	0.8355468	0.006097	137.05	<.0001*
PlayerFieldSkills	0.8623998	0.007917	108.93	<.0001*
StrengthAge	1.2575807	0.014429	87.15	<.0001*
Valuation	1.1786969	0.017975	65.57	<.0001*

Figure (11): All Possible Models using Stepwise

All Possible Models

Ordered up to best 10 models up to 5 terms per model.

Model	Number	RSquare	RMSE	AICc	BIC
Attacker	1	0.3752	5.5239	112494	112518
Defender	1	0.1939	6.2741	117074	117097
PlayerFieldSkills	1	0.1225	6.5461	118600	118623
StrengthAge	1	0.0784	6.7085	119481	119505
Valuation	1	0.0444	6.8313	120133	120157
Attacker,Defender	2	0.5691	4.5875	105815	105846
Attacker,PlayerFieldSkills	2	0.4977	4.9530	108572	108603
Attacker,StrengthAge	2	0.4536	5.1658	110085	110116
Attacker,Valuation	2	0.4196	5.3242	111171	111202
Defender,PlayerFieldSkills	2	0.3164	5.7778	114111	114143
Defender,StrengthAge	2	0.2723	5.9613	115235	115266
Defender,Valuation	2	0.2383	6.0991	116057	116088
PlayerFieldSkills,StrengthAge	2	0.2009	6.2469	116918	116950
PlayerFieldSkills,Valuation	2	0.1669	6.3785	117668	117699
StrengthAge,Valuation	2	0.1228	6.5451	118596	118627
Attacker,Defender,PlayerFieldSkills	3	0.6916	3.8811	99802.3	99841.3
Attacker,Defender,StrengthAge	3	0.6475	4.1492	102205	102244
Attacker,Defender,Valuation	3	0.6135	4.3449	103862	103901
Attacker,PlayerFieldSkills,StrengthAge	3	0.5761	4.5501	105522	105561
Attacker,PlayerFieldSkills,Valuation	3	0.5421	4.7292	106910	106949
Attacker,StrengthAge,Valuation	3	0.4980	4.9516	108563	108602
Defender,PlayerFieldSkills,StrengthAge	3	0.3949	5.4365	111922	111961
Defender,PlayerFieldSkills,Valuation	3	0.3608	5.5872	112906	112945
Defender,StrengthAge,Valuation	3	0.3167	5.7767	114105	114144
PlayerFieldSkills,StrengthAge,Valuation	3	0.2453	6.0711	115893	115932
Attacker,Defender,PlayerFieldSkills,StrengthAge	4	0.7700	3.3516	94528.3	94575.1
Attacker,Defender,PlayerFieldSkills,Valuation	4	0.7360	3.5910	97009.7	97056.5
Attacker,Defender,StrengthAge,Valuation	4	0.6919	3.8792	99786.4	99833.2
Attacker,PlayerFieldSkills,StrengthAge,Valuation	4	0.6205	4.3054	103534	103581
Defender,PlayerFieldSkills,StrengthAge,Valuation	4	0.4393	5.2334	110554	110601
Attacker,Defender,PlayerFieldSkills,StrengthAge,Valuation	5	0.8144	3.0108	90673.9	90728.5

7 REFERENCES

- Lecture Notes
- Online Learning resources