evaluating basketball players' performance using decision trees and TOPSIS

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Abstract:

Data from the Euroleague 2017-2018 season, including individual game data for each player, is examined using Decision Trees and TOPSIS algorithms. The goal of this research is to provide an alternative rating system for each position, such as guards, forwards, and centres, to identify the top and worst performers. Classification and regression problems are well-suited to the use of decision trees, a supervised learning technique. Data characteristics may be used to build a model that predicts a target variable's value using basic decision rules derived from the data. On the other hand, TOPSIS is a multi-criteria decision-making system that may be used to build a ranking system. To determine a player's rating, teams consider all of their individual statistics, including points, rebounds, assists, steals, blocks, turnovers, free throw percentage, and fouls. Decision trees and TOPSIS findings are compared to the player's Performance Index Rating (PIR) index, which is a single value that expresses the player's performance. The over- and under-performers in the 2017-2018 Euroleague season were identified by comparing these three metrics. Effective approaches such as Chernoff's faces are used to depict the consequences of individual players' performances.

INTRODUCTION:

With the advancement of computer science over the previous two decades, sports statistics have become more popular. However, employing statistical techniques to draw conclusions is a relatively recent discipline. Team and player statistics have been utilised for far longer than this. In sports, statistics are used to measure team success, forecast game results, evaluate a player or team's performance and efficiency, and rank individuals or teams. It's safe to say that basketball is a very popular sport all around the globe. The NBA was created in the United States, while the Euroleague operates in Europe. They are the two largest basketball organisations in the world. The 2017–2018 Euroleague season saw 16 teams from nine nations compete. This research focuses on the Euroleague players from the 2017–2018 season and seeks to build an alternative ranking system for the players using the TOPSIS approach.. The Euroleague website's player data from the 2017-2018 Euroleague season were used to create the new ranking system. Guards, forwards, and centres make up the three divisions of players. ANOVA analysis and decision trees are used to determine whether variables are statistically significant among groups. Those variables are given different weights. Players are ranked in a new way by the TOPSIS results. With the help of Chernoff's faces, we can see how the new rating system compares to the Euroleague's Performance Index Rating (PIR).

PREVIOUS WORKS:

Six NBA players were evaluated using the TOPSIS Multiple Criteria Decision-Making (MCDM) technique by Bozbura, Beşkese, and Kaya [1]. Data envelopment analysis was used to rank Spanish Basketball League players and generate an alternative performance measure by Cooper, Ruiz and Sirvent [2] and Cooper, Ramon and Ruiz (2011). Network analysis was utilised by Piette, Pham, and Anand [3] to analyse basketball players. Data from NBA play-by-play is utilised to identify top and bottom scorers on offence, defence, and the team as a whole. Reza The Bundesliga data from the 1999/2000 season was used by Kiani Mavi et al [4] to rate football teams using AHP and TOPSIS. For the 2011/2012 NBA season, Radovanovic and colleagues employed data envelopment analysis (DEA) and distance-based analysis (DBA) to rank 26 NBA players. Based on the 2011 season of the Chinese Professional Baseball League (CPBL), Chen, Lee, and Tsai [6] employed AHP and TOPSIS methodologies to determine which players should start in a baseball match. A team's competitiveness was assessed using the TOPSIS and grey correlation methods used by Changwu [7] on the 12 Olympic basketball teams that competed in London in 2012. Researchers Moreno and Lozano used a network-DEA technique to evaluate 30 NBA teams' efficiency during the 2009-2010 season. 35 basketball players from the Spanish League were ranked using DEA by Atefeh Masoumzadeh and Amirteimoori [9]. Using stock market data for Turkish football teams, Ergül [10] found that success in football had a beneficial effect on financial performance. " Turkish basketball teams from the Turkish Super Basketball League and the Euroleague were studied by Geyik and Eren [11]. They ranked the teams based on the TOPSIS outcomes and compared the results to the actual world.

DATA AND VARIABLES:

Players in the Euroleague are ranked according to the PIR index. A positive component of the index is defined as the number of points, rebounds, assists, and steals a team has, while a negative component is defined as the number of missed shots, turnovers, and fouls a team has. Here are the steps for calculating the PIR index.

$$PIR = \begin{pmatrix} Points + Rebounds + Assists \\ + Steals + Blocks + Fouls\ Drawn \end{pmatrix} - \begin{pmatrix} Missed\ Field\ Goals + Missed\ Free\ Throws \\ + Turnovers + Shots\ Rejected + Fouls\ Committed \end{pmatrix}$$

There are various flaws with this strategy. To begin with, it gives equal weight to every statistic, regardless of its relevance. In addition, the position of the player is not taken into consideration; some statistics, like as blocks for centres and assists for guards, are more valuable for certain positions. The TOPSIS technique seeks to address this void by allowing for varying weighting depending on their placements.

A. Data

The Euroleague's website was used to compile the players' statistics. Guards, forwards, and centres make up the three groupings of data that are broken down by position. Next, the study excludes players who spent just a few minutes on the floor. Players are eligible for this analysis if they have played at least 10 games for a minimum of 15 minutes each game. 150 players, including 62 guards, 54 forwards and 34 centerbacks are included in the study after eliminating individuals.

This research makes use of two different sets of data. A player's average statistics are included in the first set; the second set represents those same figures normalised to 40 minutes of play. The stats a player would record if he played the whole game may be determined by normalising the data for 40 minutes. This method reduces the influence of MPG on other data since when MPG rises, so do the other stats. Normalized Z scores are used in TOPSIS analysis for each location after normalisation. Using this method, several numbers that were inflated by players who played for less than 15 minutes are eliminated.

B. Variables

Selected variables reflects every aspect of the game such as shooting, rebounding, ball handling and defence and durability [2].

• Games Played (GP): Total number of games a player played through the season. This variable is related with the durability part of the game.

• Minutes Per Game (MPG): Average number of minutes a player stay on court per game. This variable is related with the durability part of the game.

• Adjusted Field Goal (AFG): AFG is an advanced metric that shows the shooting ability of a player. AFG is calculated with the given formula,

$$AFG = (PPG - FTPG) \times AFG\%$$

where PPG is points per game and FTPG is free throws made per game and AFG% is the adjusted field goal percentage which is calculated with

$$\frac{PPG - FTPG}{2 \times FGA}$$

where FGA is the number of field goal attempts. This variable is related with the shooting part of the game.

• Adjusted Free Throw (AFT): AFT is related with the shooting part of the game and is defined with

$$AFT = FTM \times FT\%$$

where *FT*% is the free throw success percentage.

• Rebounds Per Game (RPG): Average number of rebounds a player made per game. This variable is related with the rebounding part of the game.

• Assists Per Game (APG): Average number of assists a player made per game. This variable is related with the ball handling and shooting part of the game.

• Steals Per Game (SPG): Average number of steals a player made per game. This variable is related with the defence part of the game.

• Blocks Per Game (BPG): Average number of blocks a player made per game. This variable is related with the defence part of the game.

• Inverse of Turnovers (TOV_INV): Inverse of average number of turnovers a player made per game. Taking inverse of the turnovers provide consistency with other variables as normally higher turnovers indicates worse performance by a player. This variable is related with the ball handling part of the game.

• Non-Committed Fouls Own (NON_PF): Average number of non-committed fouls of a player.

$$NON\_PF = 5 - PF$$

where PF is the personal fouls. The logic behind this variable is same with the TOV_INV. This variable is related with the defence and durability part of the game.

• Fouls Received (FOUL_REC): Average number of fouls that opposition players made to the player. This variable is related with the shooting and ball handling part of the game.

METHODS:

This investigation makes use of a total of four distinct approaches. Player positions are analysed using ANOVA with Bonferroni post-hoc tests and decision trees to identify relevant characteristics After that, an alternate ranking system for basketball players is developed using the TOPSIS approach. The Chernoff faces are used to depict the final outcome. The study is carried out in R, a statistical programming language. Chernoff faces are constructed by using the faces function from the aplpack package in conjunction with the rpart and rpart.plot packages. A. Logic Diagrams Prediction, classification, and regression are all possible uses for decision trees [12]. Classifying basketball players based on their position provides insight into which basketball-related data distinguish them in this research. With this method, various places may be assigned varying weights. The simplicity and visual portrayal of decision trees makes them popular. Determination trees are composed of roots, branches, and leafs, in which the dependent variables are broken down into smaller fractions using branches and leaves. Topping the list of B. TOPSIS They called it the "TOPSIS" approach (Technique for Order Preferences by Similarity to an Ideal Solution). According to TOPSIS, the optimum option should be one which is closest to and furthest away from the perfect answer in the positive sense (the optimal solution) (inferior solution). The Euclidean distance was employed in this research as a distance measurement. The processes of TOPSIS may be summarised as follows [14] using the Euclidean distance:

Let $A = \{A_k \mid k = 1,...,n\}$ denotes set of alternatives, denotes $C = \{C_j \mid j = 1,...,m\}$ set of criteria. $X = \{X_{kj} \mid k = 1,...,n; j = 1,...,m\}$ indicates the set of performance ratings for each criteria and each alternatives where $w = \{w_j \mid j = 1,...,m\}$ is the set of weights for each criteria. Then the information table $I = (A, C, X, W)$ can be given with the following form (Table – I).

TABLE I. THE INFORMATION TABLE OF TOPSIS

Alternatives	C_1	C_2	...	C_m
A_1	X_{11}	X_{12}	...	X_{1m}
A_2	X_{21}	X_{22}	...	X_{2m}
...	...	...	...	...
A_n	X_{n1}	X_{n2}	...	X_{nm}
W	W_1	W_2	...	W_m

Step 1: Calculating the normalized ratings.

$$r_{kj}(x) = \frac{x_{kj}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}}, k = 1,...,n; j = 1,...,m. \quad (6)$$

Step 2: For the benefit criteria calculate the weighted normalized ratings with

$$v_{kj}(x) = w_j r_{kj}(x), k = 1,...,n; j = 1,...,m.$$

(7)

Step 3: Positive Ideal Point (PIS) and Negative Ideal Point (NIS) are determined with the maximum and minimum values for v_{kj} in each criterion.

$$PIS = A^+ = \{v_1^+(x), v_2^+(x),...,v_j^+(x),...,v_m^+(x)\}$$

$$NIS = A^- = \{v_1^-(x), v_2^-(x),...,v_j^-(x),...,v_m^-(x)\} \quad (8)$$

Step 4: Calculate the separation from the PIS and the NIS between alternatives.

$$D_k^+ = \sqrt{\sum_{j=1}^{m} \left[v_{kj}(x) - v_j^+(x)\right]^2}, k = 1,...,n \quad (9)$$

$$D_k^- = \sqrt{\sum_{j=1}^{m} \left[v_{kj}(x) - v_j^-(x)\right]^2}, k = 1,...,n \quad (10)$$

Step 5: The similarities to the PIS can be derived with:

$$C_k^* = D_k^- \big/ (D_k^+ + D_k^-), k = 1,...,n$$

(11)

where $C_k^* \in [0,1]$.

C. Chernoff Faces

Chernoff faces is a graphical method proposed by H. Chernoff [15] which visualizes multidimensional data by using the properties of the faces. Each aspect of a face denotes a different variable.

RESULTS:

Table I shows the raw and normalised data for the chosen variables for the 40-minute period. According to one-way ANOVA and Bonferroni test findings, positions differed in terms of rebounds, assists, blocks, and fouls received as well as per-game and per-40-minute numbers. Among positions, non-made fouls are also useful in terms of per-game statistics. Per game and 40-minute figures show that guards have more assists than wingers, but this isn't the case for forwards and centres. According to the number of non-made fouls, centre players commit more fouls than any other position. According to per game statistics, forwards get a much lower number of fouls than other positions, and each position receives a varied total based on the amount of minutes played. Fig. 1 depicts the outcomes of a decision tree depending on the location of the nodes. Similarly to ANOVA's findings, the use of assists, rebounds, blocks, and non-made fouls to distinguish between positions is successful. Table III displays the classification tree findings. In the analysis of the decision tree, it seems that guards are better at dishing out assists, while centres are better at rebounding and blocking shots. In terms of rebounding, forwards are more responsible than guards but less responsible than centres. While forwards have a lower assist total than guards, they have a higher assist total than centres. Centers also play less minutes per game and commit fewer fouls than forwards do. This information may be found in Table III.

There are separate weights for each position and also for games played and minutes played each game.

The overall decision tree accuracy is 0.87. It successfully predicted 91% of guards, 78% of forwards, and 94% of centre positions, according to the decision tree. According to Table IV, the weights of each position are listed

TABLE II. DESCRIPTIVE STATISTICS, ANOVA AND BONFERRONI TEST RESULTS FOR THE VARIABLES AMONG POSITIONS (a) PER GAME STATS (b) PER 40 MIN

	GUARDS (n=62)		FORWARDS (n=54)		CENTERS (n=34)		TOTAL (n=150)		ANOVA	
PER GAME STATS	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	p value	Source of Diff.
GP	28.10	6.42	27.80	6.53	28.12	6.02	27.99	6.33	0.960	---------
MPG	21.78	3.95	21.45	3.69	20.41	3.53	21.35	3.78	0.232	---------
AFG	4.08	1.80	3.79	1.17	4.14	0.98	3.99	1.43	0.438	---------
AFT	1.35	0.93	1.06	0.50	1.30	0.54	1.23	0.72	0.084	---------
RB	2.13	0.72	3.35	1.22	4.92	0.91	3.20	1.44	0.000***	G – FW – C
APG	2.85	1.67	1.43	0.63	1.03	0.55	1.93	1.41	0.000***	G – FW, C
SPG	0.75	0.33	0.64	0.27	0.60	0.30	0.67	0.31	0.040**	---------
TOV_INV	0.88	0.51	1.07	0.37	1.06	0.40	0.99	0.45	0.042**	---------
BPG	0.15	0.08	0.28	0.19	0.61	0.39	0.33	0.30	0.000***	G – FW – C
NON_PF	2.95	0.51	2.99	0.48	2.59	0.52	2.88	0.53	0.001***	C – G, FW
FOUL_REC	2.38	1.27	1.84	0.75	2.76	0.88	2.27	1.07	0.000***	FW – G, C

*** p < 0.001 ** p < 0.05 G: Guards, FW: Forwards, C: Centers

	GUARDS (n=62)		FORWARDS (n=54)		CENTERS (n=34)		TOTAL (n=150)		ANOVA	
PER 40 MIN STATS	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	p value	Source of Diff.
GP	------	------	------	------	------	------	-----	------	------	---------
MPG	------	------	------	------	------	------	-----	------	------	---------
AFG	7.33	2.50	7.07	1.89	8.19	1.74	7.43	2.16	0.055	---------
AFT	2.38	1.38	1.99	0.96	2.56	1.02	2.28	1.18	0.058	---------
RB	3.91	1.09	6.25	2.00	9.79	1.97	6.09	2.80	0.000***	G – FW – C
APG	5.06	2.45	2.64	0.98	1.99	0.93	3.49	2.19	0.000***	G – FW, C
SPG	1.35	0.50	1.20	0.51	1.16	0.53	1.25	0.52	0.147	---------
TOV_INV	1.75	1.30	2.12	1.04	2.14	0.82	1.97	1.12	0.132	---------
BPG	0.17	0.19	0.48	0.36	1.20	0.76	0.52	0.59	0.000***	G – FW – C
NON_PF	5.66	1.71	5.79	1.51	5.24	1.41	5.61	1.58	0.273	---------
FOUL_REC	4.22	1.74	3.44	1.36	5.47	1.68	4.22	1.76	0.000***	G – FW – C

*** p < 0.001 ** p < 0.05 G: Guards, FW: Forwards, C: Centers

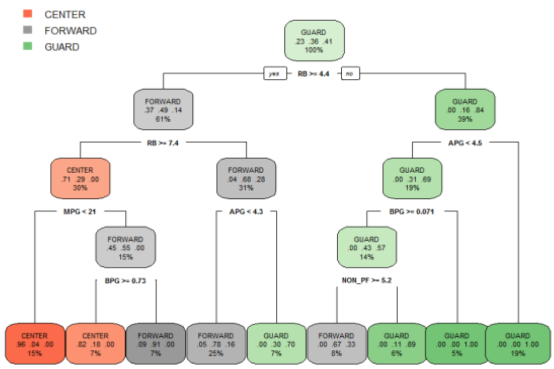

Fig. 1. Decision tree results for player positions.

TABLE III. DECISION TREE CLASSIFICATION RESULTS

TREE		PREDICTED		
	POSITION	GUARDS	FORWARDS	CENTERS
OBSERVED	GUARDS	52	10	0
	FORWARDS	4	47	3
	CENTERS	0	3	31
	SENSITIVITY	0.9286	0.7833	0.9118
	SPECIFITY	0.8936	0.9222	0.9741
	BAL. ACCURACY	0.9111	0.8528	0.9430
	OVER. ACCURACY	0.8667	KAPPA	0.795

: Guards, F: Forwards, C: Centers

For each position, the TOPSIS results for the best 10 players each game and every 40 minutes are shown in Table V. For comparison's sake, data from the 2017-2018 Euroleague season is also included in Table V. Per-game data did not vary much from the PIR index values. With the new weightings, the rankings have been fine-tuned. There is a huge discrepancy between PIR and Per 40 Minute metrics when it comes to performance index ranking especially for the forwards.

TABLE V. TOPSIS RESULTS FOR GUARDS, FORWARDS AND CENTERS PER GAME AND PER 40 MINUTES.

GUARDS									
PER GAME					PER 40 MINUTES				
NAME	C*	TOPSIS RANK	PIR	PIR RANK	NAME	C*	TOPSIS RANK	PIR	PIR RANK
SHVED, ALEXEY	0.73	1	20.38	2	CALATHES, NICK	0.61	1	25.53	4
DONCIC, LUKA	0.65	2	21.55	1	DE COLO, NANDO	0.60	2	29.38	2
DE COLO, NANDO	0.64	3	18.94	3	DONCIC, LUKA	0.60	3	33.21	1
CALATHES, NICK	0.63	4	18.52	4	JAMES, MIKE	0.58	4	24.56	6
NEDOVIC, NEMANJA	0.59	5	16.67	5	HEURTEL, THOMAS	0.57	5	23.57	7
RODRIGUEZ, SERGIO	0.57	6	13.83	11	NEDOVIC, NEMANJA	0.55	6	26.58	3
PANGOS, KEVIN	0.56	7	14.19	9	RODRIGUEZ, SERGIO	0.55	7	21.27	12
JACKSON, PIERRE	0.56	8	14.28	8	SHVED, ALEXEY	0.55	8	25.31	5
SPANOULIS, VASSILIS	0.56	9	11.88	17	ROCHESTIE, TAYLOR	0.53	9	22.09	10
JAMES, MIKE	0.55	10	15.67	6	PANGOS, KEVIN	0.52	10	20.61	14

FORWARDS									
PER GAME					PER 40 MINUTES				
NAME	C*	TOPSIS RANK	PIR	PIR RANK	NAME	C*	TOPSIS RANK	PIR	PIR RANK
GILL, ANTHONY	0.63	1	13.09	4	HANGA, ADAM	0.59	1	14.74	33
CLYBURN, WILL	0.62	2	13.61	3	NUNNALLY, JAMES	0.57	2	17.01	21
WRIGHT, DORELL	0.62	3	12.81	6	PAPAPETROU,IOANNIS	0.55	3	11.17	50
JANKUNAS, PAULIUS	0.59	4	13.71	1	GARINO, PATRICIO	0.55	4	11.98	48
MELLI, NICOLO	0.57	5	12	8	SANDERS, RAKIM	0.53	5	14.85	32
BEAUBOIS, RODRIGUE	0.56	6	10.58	14	WHITE, AARON	0.51	6	18.2	17
PAPANIKOLAOU, KOSTAS	0.56	7	11.25	9	THOMPSON, HOLLIS	0.50	7	12.89	44
HONEYCUTT, TYLER	0.55	8	12.82	5	PRINTEZIS, GEORGIOS	0.49	8	21.38	5
PRINTEZIS, GEORGIOS	0.54	9	13.68	2	SASTRE, JOAN	0.48	9	12.01	47
RUBIT, AUGUSTINE	0.54	10	12.1	7	ABALDE, ALBERTO	0.48	10	14.41	34

CENTERS									
PER GAME					PER 40 MINUTES				
NAME	C*	TOPSIS RANK	PIR	PIR RANK	NAME	C*	TOPSIS RANK	PIR	PIR RANK
VESELY, JAN	0.65	1	16.03	2	MCLEAN, JAMEL	0.57	1	25.2	9
SHENGELIA, TORNIKE	0.65	2	18.21	1	VESELY, JAN	0.48	2	24.09	16
DUNSTON, BRYANT	0.65	3	15.53	3	MILUTINOV, NIKOLA	0.55	3	25.83	7
SINGLETON, CHRIS	0.59	4	12.47	11.5	SHENGELIA, TORNIKE	0.44	4	28.58	3
AYON, GUSTAVO	0.56	5	14.22	6	HINES, KYLE	0.51	5	22.24	21
GUDAITIS, ARTURAS	0.51	6	15.41	4	DUBLJEVIC, BOJAN	0.60	6	26.43	6
HINES, KYLE	0.50	7	12.1	14	GUDAITIS, ARTURAS	0.54	7	29.8	2
AUGUSTINE, JAMES	0.48	8	14.38	5	SERAPHIN, KEVIN	0.42	8	24.59	13
MILUTINOV, NIKOLA	0.45	9	14.03	7	STIMAC, VLADIMIR	0.41	9	30.44	1
DAVIES, BRANDON	0.45	10	9.78	26	DAVIES, BRANDON	0.54	10	22.45	19.5

Fig. 2. to 4. give Chernoff Faces results for the guards,

This indicates the requirement of better weight selection for the forwards in the future studies. Other than this problem, TOPSIS results show great stability and stands as a solid alternative for the PIR inde

TABLE IV. WEIGHTS FOR EACH POSITION FOR TOPSIS

VARIABLES	WEIGHTS (PER GAME)			WEIGHTS (40 MIN)		
	G	F	C	G	F	C
GP	0.107	0.119	0.112	0.000	0.000	0.000
MPG	0.214	0.238	0.224	0.000	0.000	0.000
AFG	0.161	0.178	0.168	0.222	0.241	0.258
AFT	0.107	0.119	0.112	0.111	0.138	0.129
RB	0.054	0.079	0.093	0.111	0.172	0.215
APG	0.125	0.079	0.075	0.222	0.103	0.086
SPG	0.071	0.079	0.075	0.111	0.103	0.086
TOV_INV	0.054	0.020	0.019	0.111	0.069	0.043
BPG	0.036	0.059	0.075	0.037	0.103	0.151
NON_PF	0.036	0.010	0.009	0.037	0.034	0.022
FOUL_REC	0.036	0.020	0.037	0.037	0.034	0.011
TOTAL	1	1	1	1	1	1

G

In this case, the forwards and the centres. Each feature of the face is a representation of one or more of the following player characteristics: Height of the face – GP, width of the face – MPG, structure of the face – AFG, height of mouth – AFT, width of mouth – RB, smiling – APG, height of eyes – SPG, width of eyes – Inverse of Turnover, height of hair – BPG, width of hair – Non-made fouls, style of hair – received fouls, height of nose – GP, width of nose – MPG, width of ear – AFG, height of ear – AFT. – AFG.

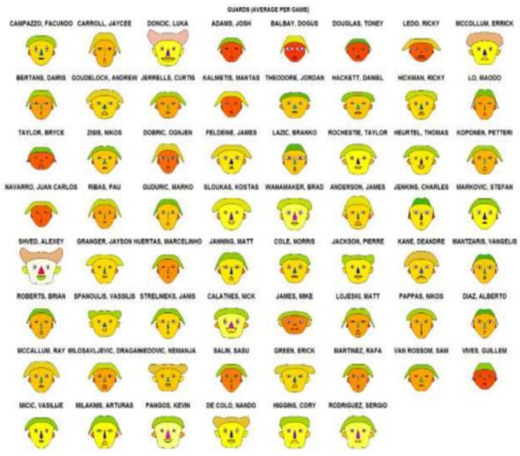

Fig. 2. Chernoff Faces for Guards

CONCLUSIONS:

In this research, individual game data for basketball players from the Euroleague 2017-2018 season are analysed using Decision Trees and TOPSIS algorithms. The goal of this research is to provide an alternative rating system for each position, such as guards, forwards, and centres, to identify the top and worst performers. Individual statistics including as points, rebounds, assists, thefts, blocks, turnovers, free throw percentage, and fouls are all utilised to identify exceptional performances. Players from Fig. 2 Luka Doncic, Alexey Shved, Nando de Colo, and Nick Calathes are initially seen in the backcourt. Will Clyburn, GeorgiozPrintezis, Antony Gill, Nicola Melli, and Edgaras Ulanovas are among the first names that come to mind when looking at the forwards (Fig. 3). For centre positions (Fig. 4), Jan Vesely, TornikaShengalia, Chris Singleton, and Bryant Dunston are the most significant players create a system for assigning players to teams. Decision trees and one-way ANOVA are used to identify the most important factors for each position, and TOPSIS findings are compared with the Performance Index Rating (PIR) index of players, which is a single number that expresses the performance of a certain player. Analyzing the differences between them indicated which Euroleague teams performed better or worse in the 2017-2018 season, and provided another method for evaluating individual players' achievements.

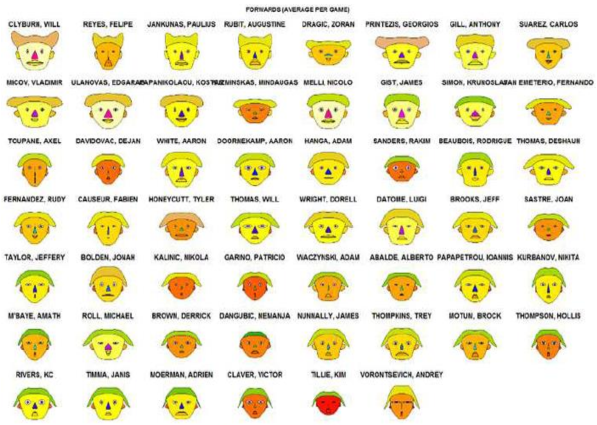

Fig. 3. Chernoff Faces for Forwards

Fig. 4. Chernoff Faces for Centers

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