

Data Science 1

Screenshots:

stats data

[illegible]

games data

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
1	id	date	home	team	period	postseason	season	status	time	visitor	team	home	team	home	team	home	team	visitor	team	visitor	team	visitor	team	home
2	8779	1992-04-1	104	4	FALSE	1991	Final		110	22	ORL	Orlando	East	Southeast	Orlando M	Magic	3	BKN	Brooklyn	West	Atlantic	Brooklyn I	Nets	
3	8780	1992-04-1	122	4	FALSE	1991	Final		100	24	PHX	Phoenix	West	Pacific	Phoenix S	Suns	21	OKC	Oklahoma	East	Northwest	Oklahoma	Thunder	
4	8781	1993-03-03	125	4	FALSE	1992	Final		115	24	PHX	Phoenix	West	Pacific	Phoenix S	Suns	23	PHI	Philadelphia	East	Atlantic	Philadelphia	76ers	
5	8782	1993-03-03	116	4	FALSE	1992	Final		97	3	BKN	Brooklyn	East	Atlantic	Brooklyn I	Nets	22	ORL	Orlando	East	Southeast	Orlando M	Magic	
6	8783	1993-03-03	101	4	FALSE	1992	Final		97	14	LAL	Los Angeles	West	Pacific	Los Angeles	Lakers	23	PHI	Philadelphia	East	Atlantic	Philadelphia	76ers	
7	8784	1994-02-02	84	4	FALSE	1993	Final		103	14	LAL	Los Angeles	West	Pacific	Los Angeles	Lakers	26	SAC	Sacramento	West	Pacific	Sacramento	Kings	
8	8785	1994-02-01	98	4	FALSE	1993	Final		100	14	LAL	Los Angeles	West	Pacific	Los Angeles	Lakers	13	LAC	LA	West	Pacific	LA Clipper	Clippers	
9	8786	1994-02-01	103	4	FALSE	1993	Final		99	11	HOU	Houston	West	Southwest	Houston R	Rockets	1	ATL	Atlanta	East	Southeast	Atlanta H	Hawks	
10	8787	1994-02-01	100	4	FALSE	1993	Final		93	9	DET	Detroit	East	Central	Detroit P	Pistons	30	WAS	Washington	East	Southeast	Washington	Wizards	
11	8788	1994-02-01	103	4	FALSE	1993	Final		106	7	DAL	Dallas	West	Southwest	Dallas M	Mavericks	25	POR	Portland	West	Northwest	Portland T	Trail Blazers	
12	8789	1994-02-01	110	4	FALSE	1993	Final		113	30	WAS	Washington	East	Southeast	Washington	Wizards	3	BKN	Brooklyn	East	Atlantic	Brooklyn I	Nets	
13	8790	1994-02-01	100	4	FALSE	1993	Final		93	29	UTA	Utah	West	Northwest	Utah Jazz	Jazz	13	LAC	LA	West	Pacific	LA Clipper	Clippers	
14	8791	1994-12-06	100	4	FALSE	1993	Final		95	25	POR	Portland	West	Northwest	Portland T	Trail Blazers	17	MIL	Milwaukee	Central	Central	Milwaukee	Bucks	
15	8792	1994-12-06	96	4	FALSE	1994	Final		101	23	PHI	Philadelphia	East	Atlantic	Philadelphia	76ers	20	NYK	New York	East	Central	New York	Knicks	
16	8793	1994-12-03	103	4	FALSE	1994	Final		90	21	OKC	Oklahoma	West	Northwest	Oklahoma	Thunder	11	HOU	Houston	West	Southwest	Houston R	Rockets	
17	8794	1994-12-03	102	4	FALSE	1994	Final		111	16	MIA	Miami	East	Southeast	Miami H	Heat	23	PHI	Philadelphia	East	Atlantic	Philadelphia	76ers	
18	8795	1994-12-03	106	4	FALSE	1994	Final		133	3	BKN	Brooklyn	East	Atlantic	Brooklyn I	Nets	24	PHX	Phoenix	West	Pacific	Phoenix S	Suns	
19	8796	1994-12-03	116	4	FALSE	1994	Final		107	25	POR	Portland	West	Northwest	Portland T	Trail Blazers	10	GSW	Golden St	West	Pacific	Golden St	Warriors	
20	8797	1994-12-01	113	4	FALSE	1994	Final		120	29	UTA	Utah	West	Northwest	Utah Jazz	Jazz	14	LAL	Los Angeles	West	Pacific	Los Angeles	Lakers	
21	8798	1994-12-01	122	4	FALSE	1994	Final		101	27	SAS	San Antonio	West	Southwest	San Antonio	Spurs	30	WAS	Washington	East	Southeast	Washington	Wizards	
22	8799	1994-12-01	105	4	FALSE	1994	Final		90	23	PHI	Philadelphia	East	Atlantic	Philadelphia	76ers	16	MIA	Miami	East	Southeast	Miami H	Heat	
23	8800	1994-12-01	99	4	FALSE	1994	Final		96	17	MIL	Milwaukee	Central	Central	Milwaukee	Bucks	23	PHI	Philadelphia	East	Atlantic	Philadelphia	76ers	
game data all																								

merged_on_8782

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[illegible][illegible][illegible]

merged_renamed

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM			
1	Urmvnm	id																																								
2	14116	1448487	6	2	1	87	6	1	40	15	8	100	4	419500	0	4	22	5	1	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	214	True	6	1	Hasidov	6	3	Ingram	F	19	200	2	
3	14117	1448488	5	2	5	40	5	2	42.1	19	8	100	4	4353600	0	4	22	5	1	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	227	Brandon	6	3	Ingram	F	19	200	2				
4	14118	1448489	2	1	6	0	0	0	50	6	3	0	0	0	20.45	1	6	7	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	153	Travis	6	10	Farron	F	19	200	2				
5	14119	1448490	1	0	2	66.7	6	4	66.7	9	6	0	0	0	27.0200	0	3	16	2	0	3	62584	2019-10-2	28	190	5	FALSE	2019	19	122	389	JJ	6	4	Flask	G	19	200	2			
6	1420	1448491	5	0	5	66.7	3	2	28.6	7	2	100	2	2.345000	0	2	8	5	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	27	Lumco	6	6	Bell	G	19	200	2				
7	1421	1448492	1	1	6	60	5	3	44.4	9	4	100	4	4.281000	4	4	15	10	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	200	Josh	6	9	Hunt	G	19	200	2				
8	1422	1448493	0	1	0	0	0	0	100	3	3	66.7	3	2	12.29	2	3	8	2	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	354	Janil	6	11	Dukar	C	19	200	2			
9	1423	1448494	2	0	2	33.3	3	1	28.6	7	2	0	0	0	12.06	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	326	E Thair	6	1	Moore	C	19	200	2			
10	1424	1448495	2	0	2	14.3	7	1	10	10	1	0	0	0	11.95	1	2	3	4	2	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	66600	Natali	6.05922	5.94398	Alexand	G	19	200	2			
11	1425	1448496	3	2	3	0	2	0	0	4	0	100	3	3	18.02	3	5	3	6	1	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	480	Kerriech	6	7	Williams	G-F	19	200	2			
12	1426	1448497	1	0	0	33.3	3	1	50	6	3	100	2	2	13.51	0	3	9	0	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	223	Frank	6	1	Johnson	G	19	200	2			
13	1427	1448498	2	0	0	3	0	0	4	71.4	7	5	0	0	0	39.36	2	1	14	5	0	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	67100	Nicola	6.05922	5.94398	Melli	F	19	200	2		
14	1428	1448499	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	66626	Jessen	6.05922	5.94398	Hearts	C	19	200	2			
15	1429	1449000	0	2	4	25	4	1	41.7	12	5	0	1	0	35.4800	0	3	11	7	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	231	George	6	10	Boake	F-C	19	200	2			
16	1430	1449001	5	1	12	40	5	2	42.3	26	11	90.9	11	0	38.0800	6	6	34	18	0	4	62584	2019-10-2	28	190	5	FALSE	2019	19	122	416	Pascal	6	3	Slalom	F	19	200	2			
17	1431	1449002	1	0	1	3	25	4	1	22.2	9	2	100	1	1	7.15400	1	6	4	0	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	189	Harc	6	7	Heard	C	19	200	2		
18	1432	1449003	6	0	4	27.3	11	3	26.7	15	4	84.6	13	11	44.5900	1	4	22	5	2	4	62584	2019-10-2	28	190	5	FALSE	2019	19	122	286	Kyle	6	1	Lewy	G	19	200	2			
19	1433	1449004	7	0	5	71.4	7	5	66.7	10	10	83.3	6	5	54.2000	0	0	34	5	2	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	493	Fred	6	0	VanVleet	G	19	200	2			
20	1434	1449005	0	0	3	0	1	0	40	10	4	83.3	6	5	5.255000	2	13	5	1	3	3	62584	2019-10-2	28	190	5	FALSE	2019	19	122	223	Serge	6	10	Boake	F-C	19	200	2			
21	1435	1449006	2	0	7	20	5	1	26.6	7	2	0	0	0	28.3800	1	2	5	8	0	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	300	Norman	6	1	Powell	F-G	19	200	2			
22	1436	1449007	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	98	Chris	6	10	Boucher	F	19	200	2			
23	1437	1449008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	66630	Tennec	6.05922	5.94398	Davis	G	19	200	2			
24	1438	1449009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	98	Chris	6	10	Boucher	F	19	200	2			
25	1439	1449010	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	243	Stanley	6	1	Johnson	F	19	200	2			
26	1440	1449011	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	226	Malcolm	6.05922	5.94398	Miller	Unknown	19	200	2			
27	1441	1449012	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	66631	Maer	6.05922	5.94398	Thomson	G	19	200	2			
28	1420	1448929	5	2	7	0	2	0	38.1	21	8	64.3	14	9	37.2100	3	3	25	10	1	3	62585	2019-10-2	13	112	4	FALSE	2019	19	102	10	Anthony	6	10	Davis	F-C	19	200	2			
29	1421	1448930	8	1	8	20	5	1	36.8	19	7	75	4	3	36.0000	1	3	28	9	1	5	62585	2019-10-2	13	112	4	FALSE	2019	19	102	237	LeBron	6	8	Jamies	F	19	200	2			
30	1422	1448931	0	2	1	0	0	0	66.7	3	2	0	0	0	17.20	0	0	0	0	0	1	62585	2019-10-2	13	112	4	FALSE	2019	19	102	306	Julius	6	1	McBee	C	19	200	2			
31	1423	1448932	0	1	6	77.8	9	7	71.4	14	10	100	1	1	132.1900	1	3	28	7	2	0	62585	2019-10-2	13	112	4	FALSE	2019	19	102	184	Danny	6	6	Green	G-F	19	200	2			
32	1424	1448933	0	0	3	40	5	2	42.8	7	2	0	0	0	24.0200	0	0	8	3	0	2	62585	2019-10-2	13	112	4	FALSE	2019	19	102	59	Way	6	2	Bradley	C	19	200	2			
33	1425	1448934	3	0	3	0	2	0	40	0	3	0	0	0	27.2300	0	0	5	0	0	1	62585	2019-10-2	13	112	4	FALSE	2019	19	102	14	Karavass	6	1	Caballero	G	19	200	2			
34	1426	1448935	1	1	3	0	0	0	33.3	3	1	100	1	1	19.02	3	4	3	6	0	0	62585	2019-10-2	13	112	4	FALSE	2019	19	102	220	Daght	6	11	Howard	C	19	200	2			
35	1427	1448936	1	0	1	30	35	1	33.3	6	2	100	1	1	18.34	0	4	1	6	0	1	62585	2019-10-2	13	112	4	FALSE	2019	19	102	18	Thom	6	1	Green	G	19	200	2			
36	1437	1448939	5	2	7	0	2	0	38.1	21	8	64.3	14	9	37.2100	3	3	25	10	1	3	62585	2019-10-2	13	112	4	FALSE	2019	19	102	10	Anthony	6	10	Davis	F-C	19	200	2			

merged_features

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM			
Urmvnm	id	name	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score	place	date	time	score
1	14116	1448487	6	2	1	87	6	1	40	15	8	100	4	419500	0	4	22	5	1	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	214	True	6	1	Hasidov	6	3	Ingram	F	19	200	2	
2	14117	1448488	5	2	5	40	5	2	42.1	19	8	100	4	4353600	0	4	22	5	1	2	62584	2019-10-2	28	190	5	FALSE	2019	19	122	227	Brandon	6	3	Ingram	F	19	200	2				
3	14118	1448489	2	1	6	0	0	0	50	6	3	0	0	0	20.45	1	6	7	0	1	62584	2019-10-2	28	190	5	FALSE	2019	19	122	153	Travis	6	10	Farron	F-C	19	200	2				
4	14119	1448490	1	0	2	66.7	6	4	66.7	9	6	0	0	0	27.0200	0	3	16	2	0	3	62584	2019-10-2	28	190	5	FALSE	2019	19	122	389	JJ	6	4	Flask	G	19	200	2			
5	1420	1448491	1	1	6	60	5	3	44.4	9	8	100	4	4	28.9100	4	4	15	10	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	208	Brandon	6	4	Flask	G	19	200	2			
6	1421	1448492	1	1	6	60	5	3	44.4	9	8	100	4	4	28.9100	4	4	15	10	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	208	Brandon	6	4	Flask	G	19	200	2			
7	1422	1448493	1	1	6	60	5	3	44.4	9	8	100	4	4	28.9100	4	4	15	10	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	208	Brandon	6	4	Flask	G	19	200	2			
8	1423	1448494	2	0	2	33.3	3	1	25.6	7	0	0	0	0	12.6	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	626	Brandon	6	4	Flask	G	19	200	2			
9	1424	1448495	2	0	2	33.3	3	1	25.6	7	0	0	0	0	12.6	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	626	Brandon	6	4	Flask	G	19	200	2			
10	1425	1448496	2	0	2	33.3	3	1	25.6	7	0	0	0	0	12.6	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	626	Brandon	6	4	Flask	G	19	200	2			
11	1426	1448497	3	2	3	30	0	2	0	0	4	0	100	3	3	102	3	5	3	6	1	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	480	Brandon	6	7	Flask	G	19	200	2		
12	1427	1448498	3	2	3	30	0	2	0	0	4	0	100	3	3	102	3	5	3	6	1	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	480	Brandon	6	7	Flask	G	19	200	2		
13	1428	1448499	1	0	0	33.3	3	1	25.6	7	0	0	0	0	12.6	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	721	Brandon	6	3	Flask	G	19	200	2			
14	1429	1448500	1	0	0	33.3	3	1	25.6	7	0	0	0	0	12.6	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	721	Brandon	6	3	Flask	G	19	200	2			
15	1430	1448501	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
16	1431	1448502	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
17	1432	1448503	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
18	1433	1448504	5	1	12	40	5	2	42.3	26	9	0	1	10	38.0800	6	6	34	18	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	646	Brandon	6	3	Flask	G	19	200	2		
19	1434	1448505	5	1	12	40	5	2	42.3	26	9	0	1	10	38.0800	6	6	34	18	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	646	Brandon	6	3	Flask	G	19	200	2		
20	1435	1448506	5	1	12	40	5	2	42.3	26	9	0	1	10	38.0800	6	6	34	18	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	646	Brandon	6	3	Flask	G	19	200	2		
21	1436	1448507	6	0	4	27.3	1	3	26.7	9	5	86	13	11	44.5900	1	4	22	5	2	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	288	Brandon	6	1	0	0	0	196	2		
22	1437	1448508	7	0	5	71.4	7	5	68	10	18	13	3	6	54.4200	0	0	34	5	2	2	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	498	Brandon	6	0	1	0	0	17	200	2	
23	1438	1448509	7	0	5	71.4	7	5	68	10	18	13	3	6	54.4200	0	0	34	5	2	2	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	498	Brandon	6	0	1	0	0	17	200	2	
24	1439	1448510	2	0	7	30	5	1	26.6	7	0	0	0	0	28.8900	0	0	15	5	6	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	380	Brandon	6	4	Flask	G	19	200	2		
25	1440	1448511	0	0	0	33.3	3	1	25.6	7	0	0	0	0	12.6	1	0	5	3	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
26	1441	1448512	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
27	1442	1448513	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
28	1443	1448514	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
29	1444	1448515	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
30	1445	1448516	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
31	1446	1448517	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
32	1447	1448518	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
33	1448	1448519	5	2	7	30	5	2	38.1	11	64.3	14	3	9	37.2100	3	3	25	10	1	3	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	380	Brandon	6	4	Flask	G	19	200	2		
34	1449	1448520	5	2	7	30	5	2	38.1	11	64.3	14	3	9	37.2100	3	3	25	10	1	3	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	380	Brandon	6	4	Flask	G	19	200	2		
35	1450	1448521	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
36	1451	1448522	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
37	1452	1448523	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
38	1453	1448524	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
39	1454	1448525	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
40	1455	1448526	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
41	1456	1448527	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62584	2019-10-2	28	190	5	FALSE	2019	19	122	683	Brandon	6	3	Flask	G	19	200	2			
42	1457	1448528	0	0	0	0	0																																			

player_three_point_made, player_field_goal_pct, player_field_goal_attempts, player_field_goal_made, player_free_throw_pct, player_free_throw_attempts, player_free_throw_made, player_minutes_played, player_offensive_rebounds, player_personal_fouls, player_points, player_total_rebounds, player_steals, turnover, game_id, game_date, game_home_team_id, game_home_team_score, game_period, game_postseason, game_season, game_time, game_visitor_team_id, game_visitor_team_score, player_id, player_position, player_team_id, player_weight_pounds, team_id, team_division, team_full_name, home_team_conference, home_team_division, home_team_full_name, visitor_team_conference, visitor_team_division, visitor_team_full_name, team_won, abs_score_difference, player_full_name, player_height_cm, home_player_stats, player_efficiency, player_three_to_throw_attempt_ratio, player_three_to_throw_made_ratio

List of new features:

player_efficiency: This feature represents the player's efficiency in the game. It is calculated by summing the player's points, total rebounds, assists, steals, and blocks, and then subtracting the missed field goal attempts, missed free throw attempts, and turnovers. A higher value indicates a more efficient performance by the player.

player_three_to_throw_attempt_ratio: This feature represents the ratio of three-point attempts to total field goal attempts by the player. It is calculated by dividing the number of three-point attempts by the number of total field goal attempts. It provides insight into the player's preference for shooting three-pointers compared to other types of field goals.

player_three_to_throw_made_ratio: This feature represents the ratio of three-point made shots to total field goals made by the player. It is calculated by dividing the number of three-point made shots by the number of total field goals made. It gives an indication of the player's accuracy and success rate in making three-point shots compared to other types of field goals.

These features provide additional insights into the player's overall performance, shooting tendencies, and efficiency on the court.

Answers to questions:

The team with the most wins is: ('Los Angeles Lakers', 46)

The team with the least wins is: ('Charlotte Hornets', 31)

Total LA Lakers points: 10297

Total Charlotte Hornets points: 6687

a. Supervised learning refers to the type of machine learning where the model is trained on labeled data, where the input data is paired with corresponding target labels. The goal is to learn a mapping function that can predict the labels for new, unseen data. Some use cases for supervised learning include email spam classification, sentiment analysis, and image recognition.

Unsupervised learning, on the other hand, involves training a model on unlabeled data without any predefined target labels. The model learns patterns, structures, or relationships within the data without specific guidance. Use cases for unsupervised learning include clustering similar documents, customer segmentation, and anomaly detection.

b. Structured data refers to data that is organized and well-defined, typically stored in databases or structured file formats. It has a fixed schema and follows a consistent format, making it easy to analyze using traditional database operations. Use cases for structured data include financial transactions, sales records, and sensor data from IoT devices.

Unstructured data, on the other hand, does not adhere to a specific schema or format. It includes text documents, images, audio files, videos, social media posts, etc. Analyzing unstructured data requires specialized techniques such as natural language processing, computer vision, or audio processing. Use cases for unstructured data include social media sentiment analysis, image recognition, and speech-to-text conversion.

c. The Cross Industry Standard Process for Data Mining (CRISP-DM) is a widely used data mining process model. The main steps of CRISP-DM are:

Business Understanding: Understand the project objectives, requirements, and constraints from a business perspective. Define the data mining problem and set goals.

Data Understanding: Gather and explore the available data to gain insights into its structure, content, and quality. Identify any data issues or limitations.

Data Preparation: Select, clean, and transform the data to create a suitable dataset for modeling. This involves tasks like handling missing values, encoding categorical variables, and normalizing data.

Modeling: Select appropriate modeling techniques and build a predictive or descriptive model based on the prepared dataset. This step includes model training, validation, and evaluation.

Evaluation: Assess the quality and effectiveness of the developed model. Evaluate its performance against the project objectives and requirements.

Deployment: Deploy the model into a production environment, integrating it with existing systems or processes. Monitor the model's performance and make necessary adjustments.

Some use cases include customer churn prediction, fraud detection, and market basket analysis.

d. A feature vector is a representation of an object or data point in a machine learning model. It is a numerical representation that captures the relevant characteristics or features of the data. Feature vectors are used as input to machine learning algorithms for training and making predictions.

In general, feature vectors can be used to represent various types of data, such as text documents (bag-of-words representation), images (pixel values or extracted features), or audio signals (MFCC coefficients). In the preprocessed data, feature vectors can be derived from the extracted features of the basketball game data, such as player statistics, team performance metrics, or game-related attributes.

Some use cases of feature vectors include sentiment analysis of text, image classification, and speech recognition.

e. Feature engineering is the process of creating new features or transforming existing features to improve the performance of machine learning models. It involves selecting, combining, or deriving features that capture the most relevant information from the data.

In general, feature engineering aims to enhance the predictive power of the model, reduce overfitting, and improve generalization. It can involve techniques like feature scaling, one-hot encoding, feature extraction, or feature selection. In the preprocessed data, feature engineering could include creating derived

features like player efficiency, three-point-to-field-goal attempt ratio, or any other