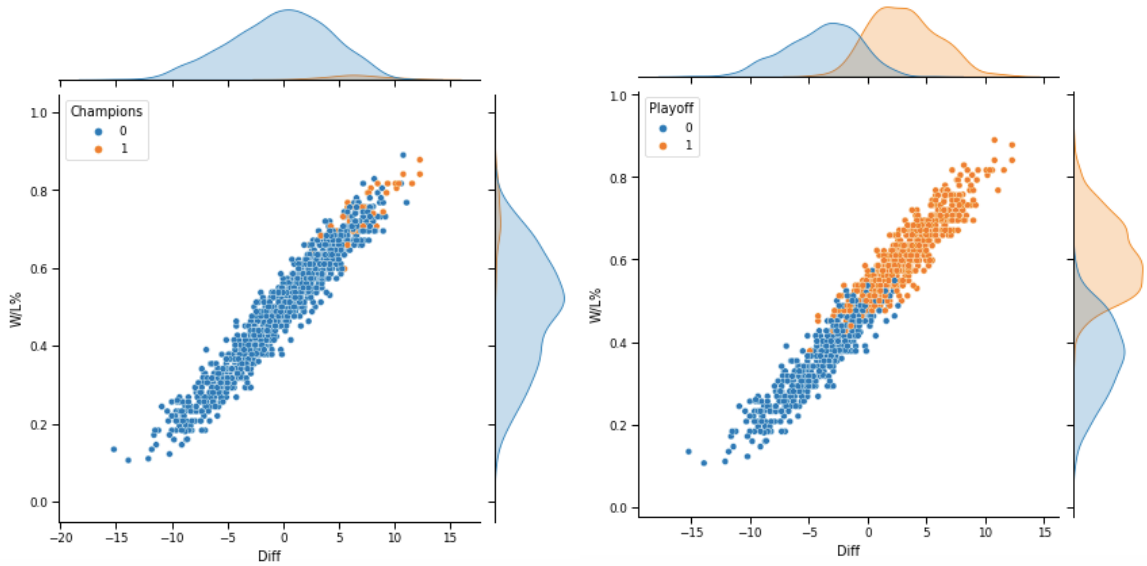
I really enjoy the NBA and wanted to explore how teams over or underperform based on their record at the end of the season and then use this sort of data to predict playoff/champion teams in the 2020-2021 season. To do this, I web scraped data from basketball-reference.com using Python from 1972 to 2019, which resulted in a dataframe with the following data:

	Team	W	L	W/L%	GB	PS/G	PA/G	SRS	Year	Playoff	Diff	Champions
0	Cleveland Cavaliers*	57	25	0.695	—	104.3	98.3	5.45	2016	1	6.0	1
1	Toronto Raptors*	56	26	0.683	1.0	102.7	98.2	4.08	2016	1	4.5	0
2	Miami Heat*	48	34	0.585	9.0	100.0	98.4	1.50	2016	1	1.6	0
3	Atlanta Hawks*	48	34	0.585	9.0	102.8	99.2	3.49	2016	1	3.6	0
4	Boston Celtics*	48	34	0.585	9.0	105.7	102.5	2.84	2016	1	3.2	0
...	...	...	...	...	...	...	...	...	...	...	...	...
11	Portland Trail Blazers	41	41	0.500	15.0	90.7	92.0	-0.58	2004	0	-1.3	0
12	Golden State Warriors	37	45	0.451	19.0	93.3	94.0	-0.07	2004	0	-0.7	0
13	Seattle SuperSonics	37	45	0.451	19.0	97.1	97.8	0.02	2004	0	-0.7	0
14	Phoenix Suns	29	53	0.354	27.0	94.2	97.9	-2.94	2004	0	-3.7	0
15	Los Angeles Clippers	28	54	0.341	28.0	94.8	99.4	-3.74	2004	0	-4.6	0

1257 rows × 12 columns

A lot of useful data here, including points scores per game (ps/g), points allowed per game (pa/g), the difference between those two (Diff), and whether that team won the championship (Champions) or went to the playoffs (Playoff). I wanted to focus on two variables: Diff and the win/less percentage (W/L%). Why? Those seem like good predictors of performance. If you score more than your opponent often, your diff will be high and your subsequence W/L would be high. Let's look at some jointplots of these variables along with grouping by Champions/Playoffs:



About what you would expect: champions and those that made the playoff are further to the top right. But it looks like my predictors could be simplified quite a bit. I used principle component analysis (PCA) to reduce my two dependent variables to just be one:

```
[9]  variables = ['W/L%','Diff']
     X = total_data[variables]
     y = total_data['Playoff']
```

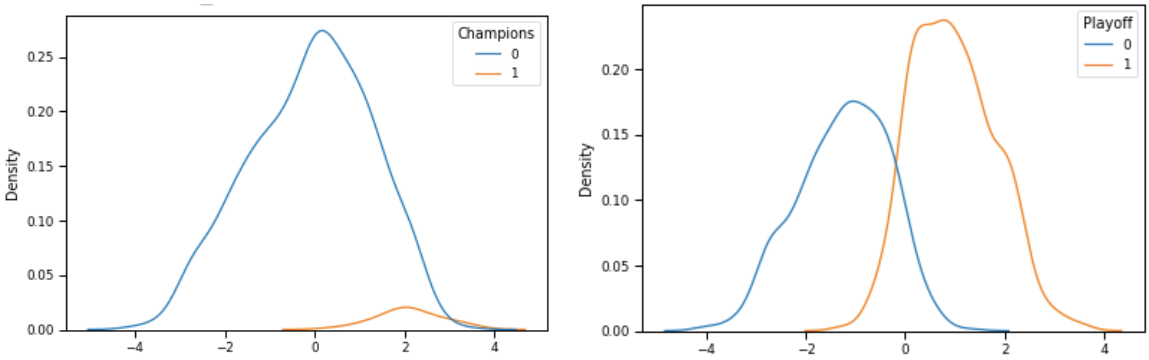
```
[10] scaler = StandardScaler()
     X_array = scaler.fit_transform(X)
     X2 = pd.DataFrame(X_array,columns=X.columns)

     pca = PCA()
     x_pca = pca.fit_transform(X2)
```

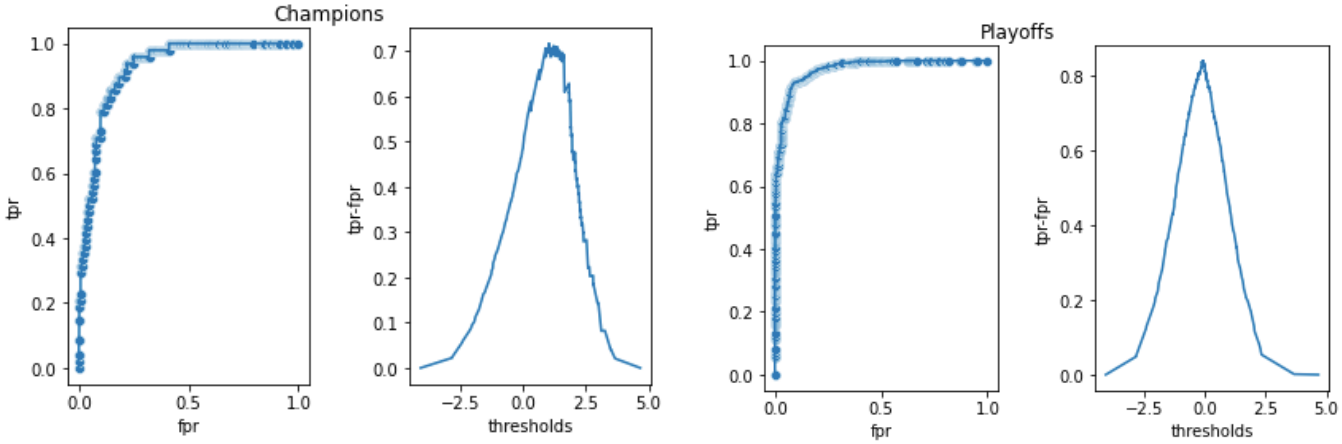
```
[ ]  pca.explained_variance_ratio_

     array([0.98410355, 0.01589645])
```

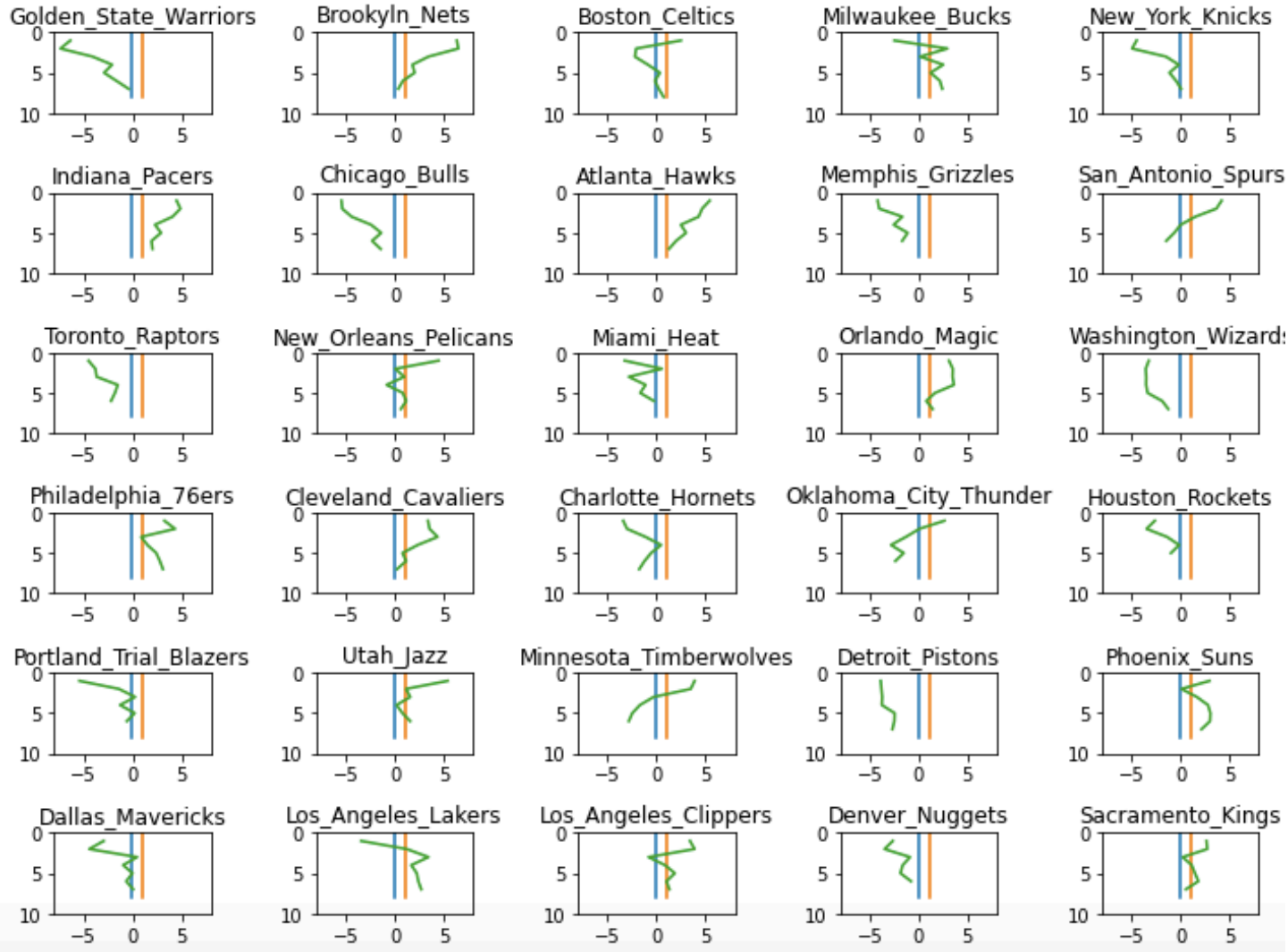
The first component explains much of the variance in the two variables. We can then look at our single component as a predictor of champion/playoff



Looks pretty good. I can then use this data to create a criterion for determining how likely a team will be a champion or playoff. I did this by looking at ROC and finding the maximum difference between the true positive rate (tpr) and false positive rate (fpr):



This creates criterions of 1.04 for champions and -0.06 for playoffs. Let's now get the boxscores for teams in the 2020-2021 season, calculate Diff and W/L% game-by-game, then pass those values into the PCA to see which teams are crossing these criterions:



Now, this is only scores of games up to 01/04/2021, so there is still quite a bit of variance. However, up to this point, its pretty clear the Lakers, 76ers, Bucks, and Suns all seem to be trending in the right direction, which more or less matches the eye-test.

The next thing to do with this data, other than track 2020-2021 season, is to see which teams most over and under performed between 1972-2019. Based on the residuals of the Diff and W/L% from the scatterplots above, see below for the under and over achievers:

```
[ ] total_data[total_data['Residuals2'] < -.10268227] # underachievers
```

	Team	W	L	W/L%	GB	PS/G	PA/G	SRS	Year	Diff	Champions	Residuals2	P-W/L%	P-W
12	Dallas Mavericks	24	58	0.293	41.0	102.3	105.4	-2.70	2018	-3.1	0	-0.107036	0.400036	32.802922
3	Philadelphia 76ers*	35	31	0.530	4.0	93.6	89.4	3.59	2012	4.2	0	-0.105348	0.635348	41.932990
8	Houston Rockets	32	50	0.390	15.0	107.4	107.6	-0.34	1974	-0.2	0	-0.103516	0.493516	40.468314
4	Chicago Bulls	24	58	0.293	14.0	95.9	98.8	-2.89	1976	-2.9	0	-0.113483	0.406483	33.331570
12	Phoenix Suns	34	48	0.415	19.0	104.9	104.2	0.64	1977	0.7	0	-0.107527	0.522527	42.847229
3	Milwaukee Bucks	38	44	0.463	10.0	114.1	111.8	2.12	1979	2.3	0	-0.111103	0.574103	47.076410
12	Seattle SuperSonics	31	51	0.378	31.0	104.4	104.5	-0.47	1986	-0.1	0	-0.118739	0.496739	40.732638

```
[ ] total_data[total_data['Residuals2'] > 0.09600996] # overachievers
```

	Team	W	L	W/L%	GB	PS/G	PA/G	SRS	Year	Diff	Champions	Residuals2	P-W/L%	P-W
7	Golden State Warriors*	51	31	0.622	18.0	108.2	107.4	0.92	1972	0.8	0	0.096249	0.525751	43.111553
2	Boston Celtics*	44	38	0.537	6.0	104.5	106.5	-1.90	1977	-2.0	0	0.101506	0.435494	35.710484
11	Los Angeles Clippers	32	50	0.390	30.0	108.6	115.5	-6.83	1986	-6.9	0	0.112456	0.277544	22.758615
4	Miami Heat*	38	44	0.463	13.0	105.0	109.2	-3.94	1992	-4.2	0	0.098422	0.364578	29.895360
6	Dallas Mavericks	11	71	0.134	44.0	99.3	114.5	-14.68	1993	-15.2	0	0.124003	0.009997	0.819735
8	Phoenix Suns*	59	23	0.720	—	110.6	106.8	3.86	1995	3.8	0	0.097546	0.622454	51.041268
12	Charlotte Hornets*	54	28	0.659	15.0	98.9	97.0	2.13	1997	1.9	0	0.097791	0.561209	46.019115

The next step is to go game-by-game and see what happened. Was it luck? Stay tuned!