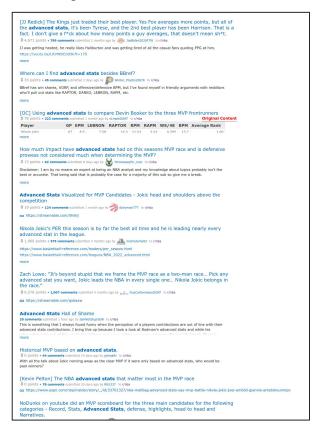
Ranking NBA statistics using XGBoost Classification

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https://github.com/genezaleski/classify_nba_stats

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Why evaluate NBA Statistics like this?



- NBA discourse has become saturated with "Advanced Stats" attempting to quantify a player/team's overall performance.
- These stats can be interpreted in many different ways, so there is a lot of noise about how they can be accurately used.
- Why should you care?
 - If you are involved in any sports discussion, you likely will see these stats cited in comparisons or rankings.
 - If you care more about the analytics aspect of these stats, this is a test of the models professional data scientists have created.
 - Data literacy is very important!
- What is original about this research?
 - I am essentially creating a new statistic, which evaluating the effectiveness of other statistics.

Why evaluate NBA statistics like this? - Problem Statement/Approach

Problem: In an effort to sort through all the noise regarding nba statistics, I
wanted to rate each of these statistics.

Approach:

- Since these stats are used so frequently to decide who is the best at X, rating these stats requires knowing which stats can accurately predict who is the best at X.
- Using XGBoost classification, we can use any statistic to classify achievements of measures of success in the NBA, then rank said statistic by their classification accuracy.

Data Collection and Cleaning

- https://www.nba.com/stats/players/advanced/ contains nba advanced stats for both players and teams dating back to 1996.
- Their API allows for requests to be made directly to endpoints retrieving advanced and basic stats for both players and teams.
- You can download stats as csv for every year available by specifying it in a url via requests python library

Data Collection and Cleaning (Example)

 Iterate over all years, replace year in endpoint, and convert returned json to csv

```
yearString = str(ii) + "-" + str(upperYear)
currURL = url.replace("2021-22", yearString)

if not exists("/home/gene/Documents/DataMiningII/Project/getNBAcom/teamAdvancedCSV/"+ yearString +"_regular.csv"):
    response = requests.get(currURL, headers=header)
    response_json = response.json()
    frame = pd.DataFrame(response_json['resultSets'][0]['rowSet'])
    frame.columns = response_json['resultSets'][0]['headers']
    frame.to_csv("/home/gene/Documents/DataMiningII/Project/getNBAcom/teamAdvancedCSV/"+ yearString +"_regular.csv",sep=",",header=frame.columns)
```

Data Collection and Cleaning

- The next step of the process was to combine all scraped data into master datasets, one for each of these four categories: player, player playoffs, team, team playoffs.
- For each of the above categories:
 - CSV for each year were combined to join advanced and regular stat CSVs by columns, yielding close to 100 unique stats.
 - Assign new "Year" column to maintain order of stats.
 - Combine all CSV for each year into one.

Assigning Labels for measures of success

```
/usr/bin/sh
file=$1
filteredFile=Sfile" filtered"
#Get correctly formatted columns
awk '{print $1 " " $2 "," $4 " " $5}' $file > $filteredFile
# replace newlines with commas
sed -zi 's/\n/,/g;s/,$/\n/' $filteredFile
# replace duplicate commas
sed -i "s+,\s++q" $filteredFile
# new line on years starting with 2
sed -i "s+,2+\n2+g" $filteredFile
# new line on years starting with 1
sed -i "s+,1+\n1+q" $filteredFile
# destroy the evidence
rm $file
mv $filteredFile $file
```

- Basketball is often hard to quantify, as there are many variables contributing to various outcomes.
- To attempt to account for this, we can look at multiple different measures of success to see how accurate statistics classify multiple contexts.
 - Players were classified as All Stars, MVPs, or Finals MVPs.
 - o Teams were classified into Finals winners and losers.
 - I didn't find any good sites to scrape this information from, so I just copied lists from ESPN.com and used awk, sed, etc. to format my this data into lists of names and years in CSV format.

022,LeBron James,Giannis Antetokounmpo,Stephen Curry,DeMar DeRozan,Mikola Jokic,Luka Doncic,Darius Garland,Ghris Paul,Jimny Butler,Donovan Mitch Il,Fred Wantlvet,Jarrett Allen,Doel Embidd,Ja Morant,Jayson Tatum,Trae Young,Andrew Wiggins,Devin Booker,Karl-Anthony Towns,Zach LaVine,Dejounte Murray,Khris Middleton,LaMelo Ball,Rudy Gobert

Assigning Labels for measures of success

- Once lists of names and years for the players and teams were formatted, I
 could assign labels of 1 and 0 for matching columns when a player or team
 achieved said success.
- Assigned labels where indices of CSV matched Names & Years.

```
with open(champpath,'r') as allStarsFile:
    for line in allStarsFile:
        allStars = line.split(",")
        year = int(allStars[0].strip())
        allStars = allStars[1:]
        for player in allStars:
            nidx = teamRegularSeason[teamRegularSeason['TEAM NAME']==player.strip()].index.values
            yidx = teamRegularSeason[teamRegularSeason['YEAR']==year].index.values
            nidx1 = teamPlayoffs[teamPlayoffs['TEAM_NAME']==player.strip()].index.values
            yidx1 = teamPlayoffs[teamPlayoffs['YEAR']==year].index.values
            reqIdx = np.intersect1d(nidx, yidx)
            playoffIdx = np.intersect1d(nidx1,yidx1)
            if regIdx.size > 0:
                teamRegularSeason['WIN'][regIdx[0]] = 1
            if playoffIdx.size > 0:
                teamPlayoffs['WIN'][playoffIdx[0]] = 1
```

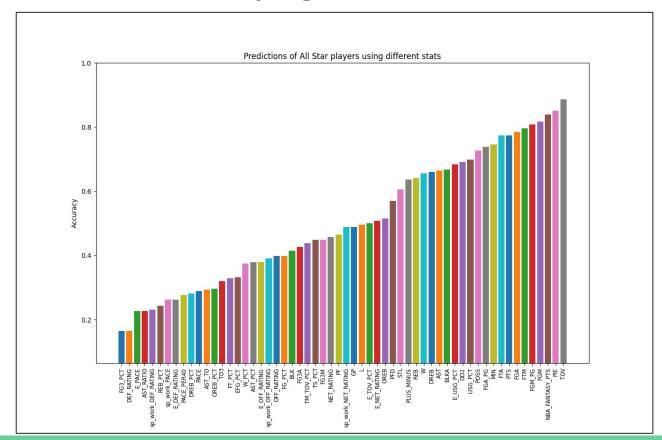
Data Classification

- With clean, labelled data, classification is now possible.
- Because there are limited amounts of "True" entries in my testing data (i.e. only 25/~12300 players in the data are labelled MVP), SMOTE was utilized to increase the number of entries labelled "True" in the data.
- Used XGBoost in Python.
 - O Why XGBoost?
 - Data is highly structured.
 - Dataset is small(ish)
 - XGBoost is the fastest and most accurate Classification technique for structured data.
- Iterated over all stats, fit XGBoost with said stat and labels, then compared the accuracy!

Data Classification (example)

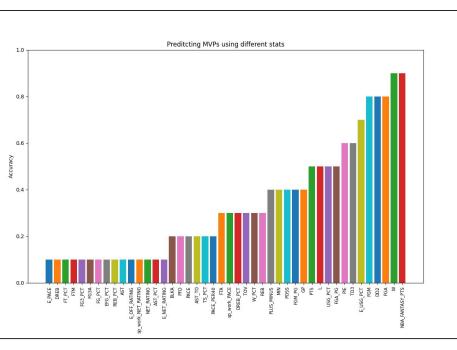
```
y = data[label]
oversample = BorderlineSMOTE()
for columnName,columnData in data.iteritems():
                      if columnName in drops:
                                           continue
                     elif "Unnamed" in columnName:
                                           continue
                      elif columnName == label:
                                           continue
                      print(columnName)
                      X = data[columnName]
                      X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = t_{\text{rain}}, t_{\text{est}}, y_{\text{random}}, x_{\text{test}}, y_{\text{train}}, y_{\text{test}}, y_{\text{test}}
                      X_train,y_train = oversample.fit_resample(X_train.to_frame(),y_train)
                      xg = XGBClassifier()
                      xg.fit(X_train.squeeze(),y_train)
                      predictions = xq.predict(X test)
                      out = classification_report(y_test,predictions,output_dict=True)
                      accuracies.append(out['accuracy'])
                      stats.append(columnName)
```

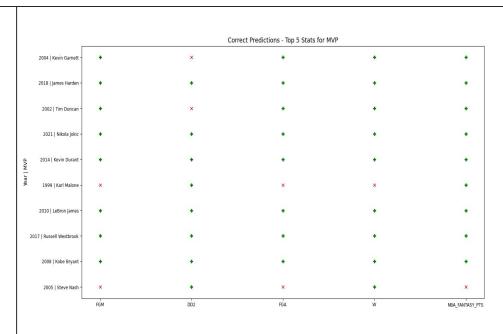
Results - Classifying All-Stars



- To yield a legitimate accuracy, predictions were only evaluated for True Positives, False Negatives.
- Certain stats were not considered due to them being duplicates (PIE_RANK is not evaluated, only PIE.)

Results - Classifying MVPs

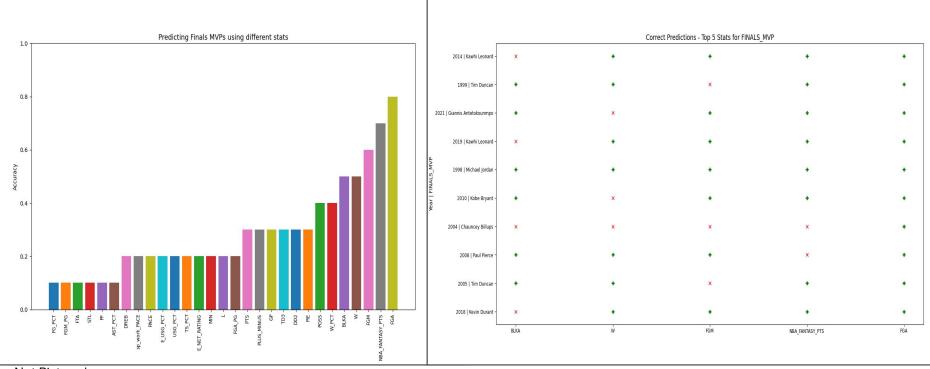




Not Pictured:

sp_work_OFF_RATING,E_DEF_RATING,DEF_RATING,sp_work_DEF_RATING,AST_PCT,AST_RATIO,OREB_PCT,T M_TOV_PCT,E_TOV_PCT,FG3M,OREB,STL,BLK,PF

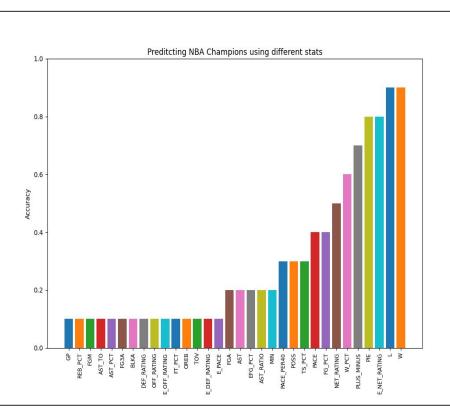
Results - Classifying Finals MVPs

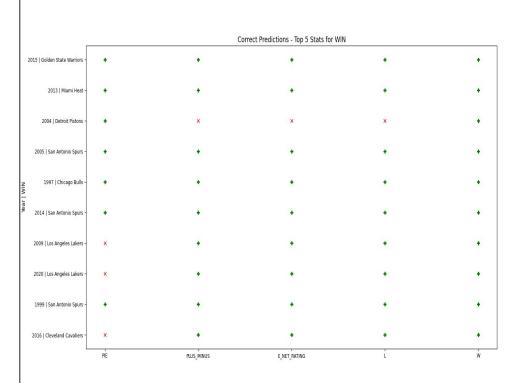


Not Pictured:

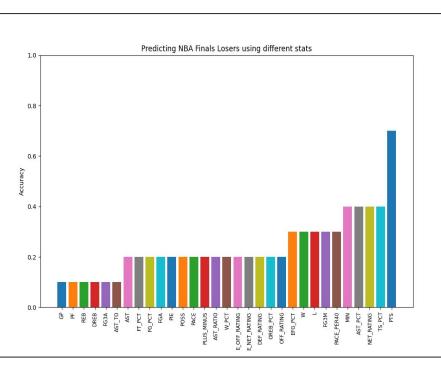
E_OFF_RATING,OFF_RATING,sp_work_OFF_RATING,E_DEF_RATING,DEF_RATING,sp_work_DEF_RATING,NET_RATING,sp_work_NET_RATING,OREB_PCT,R EB PCT,TM TOV PCT,E TOV PCT,EFG PCT,CFID,FG3M,FG3A,FG3 PCT,FTM,FT PCT,OREB,REB,AST,TOV,BLK,PFD

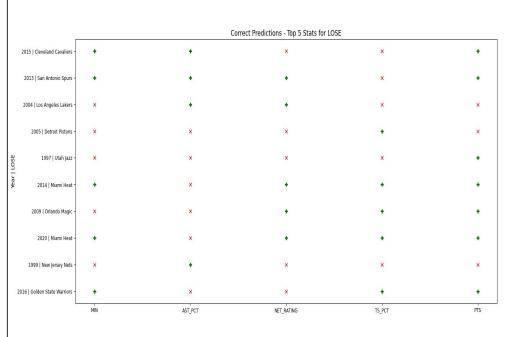
Results - Classifying NBA Champions





Results - Classifying NBA Finals Losers





Not Pictured:

E_DEF_RATING,AST_TO,DREB_PCT,REB_PCT,TM_TOV_PCT,E_PACE,FGM,FG3A,FG3_PCT,FTM,FTA,OREB,TOV,STL,BLK,BLKA,PFD

Conclusion

- A majority of stats by themselves cannot accurately predict a measure of success in the NBA.
- Many that can are basic counting stats, or combinations of said stats (i.e. fantasy points)
- "Advanced" Statistics that do perform well are ranked highly for a reason. Stats such as PIE, Net Rating, etc. have been curated by data scientists for this purpose, but still are not an end-all-be-all for NBA rankings and comparisons.