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1 NBA Standings Prediction w/ Playoff Simulation

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This notebook uses a very basic linear regression model to predict the 2020-21 NBA Standings. It uses a variety of features and is trained on the 82-game season in 2017-18.

```
- The first model uses all variables, just to use as a baseline.

- The second removes potential multicollinear variables, which improves the performance of the model.
```

The second part of this notebook invoves a Microsoft Excel simulation of the playoffs. That file will be attached to this GitHub repo along with all the data I used here.

2 Imports, Loading Data, Data Preprocessing

data sources:

- 2017-18 Team Stats (https://www.nba.com/stats/teams/advanced/?sort=W&dir=-1&Season=2017-18&SeasonType=Regular%20Season)
- 2017-18 Roster Breakdown (https://basketball.realgm.com/nba/transactions/composition_search?custom=4123)
- 2020-21 Team Stats (https://www.nba.com/stats/teams/advanced/?sort=W&dir=-1)
- 2020-21 Roster Breakdown (https://basketball.realgm.com/nba/transactions/composition_search)

In [1]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import math
import numpy as np
from scipy import stats
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

%matplotlib inline
```

```
C:\Users\student\Anaconda3\lib\site-packages\statsmodels\tools\_testing.py:19: FutureWarning: pandas.util.t
esting is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

2.1 Load Data

In [2]:

```
df1old = pd.read_csv('2017-18data1.csv')
df2old = pd.read_csv('2017-18data2.csv')
```

Data Cleaning

In [3]:

```
df1old = df1old.rename(columns={"TEAM": "Team"})
df1old['Team'] = df1old['Team'].replace(['LA Clippers'],'Los Angeles Clippers')
df2old['Team'] = df1old['Team'].replace(['Philadelphia Sixers'],'Philadelphia 76ers')
df2old = df2old.dropna(axis=1)
```

In [4]:

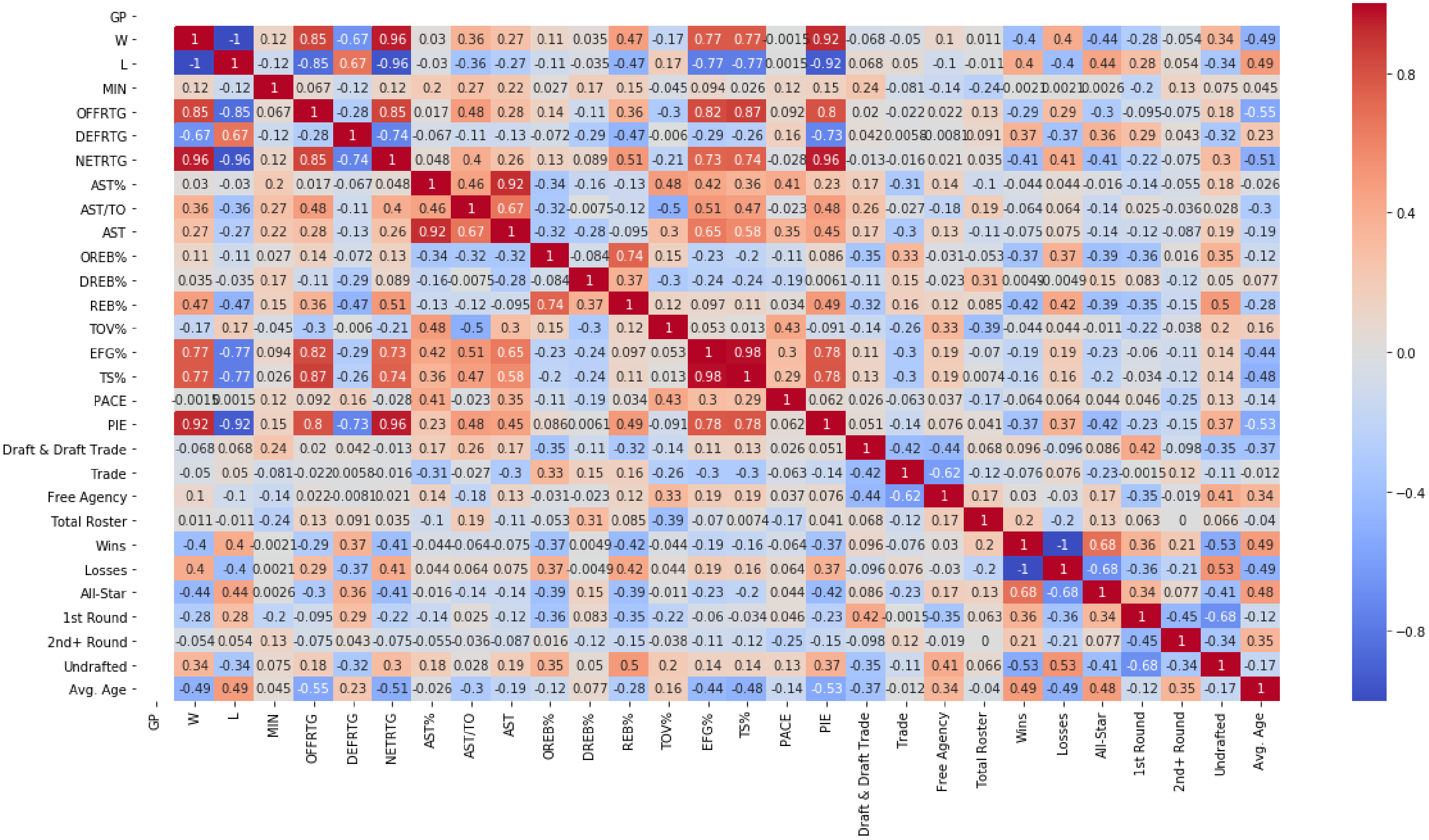
```
dfold = pd.merge(df1old,df2old,on='Team', how='inner') # merging our two dataframes
#df = df.drop('Unnamed: 20', axis=1) # sometimes this column shows up, uncomment this line if you need to

dfold = dfold.drop('MVP', axis=1) # can't decide on MVP until after the season, not a good predictive variab
dfold = dfold.sort_values('Team') # sort by team name for ease of joining predicted values back to the dataf

# unsure if i need this line yet
#dfvars = dfold.drop(['W', 'Team', 'POSS', 'L', 'Wins', 'Losses', 'Team Achievement'], axis=1).values
```

3 First Model

3.1 Correlation Heatmap (no variables dropped)

```
In [5]:  plt.subplots(figsize=(20,10))
         sns.heatmap(dfold.corr(), cmap= 'coolwarm', annot=True)
```

```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1f204971208>
```



interesting note

- avg age 65% correlation with wins

3.1.1 Multicollinearity - Variables to Remove

- MIN 95% w/ GP
  - we'll remove GP since it's less correlated with wins (target)

- OFFRTG w/ EFG%
  - OFFRTG slightly higher correlated w/ wins, we'll drop EFG%
- OFFRTG w/ TS%
  - same correlation w/ wins, we'll just drop TS%
- OFFRTG w/ PIE
  - PIE more correlated w/ wins

- NETRTG w/ PIE
  - PIE less correlated, will be dropped

- AST% w/ AST Ratio
  - drop AST%

- DEFREB% w/ REB%

- DEFREB% w/ OFFREB%
    - let's keep REB% since it has higher correlation w/ wins than the other two

- NETRTG w/ OFFRTG
    - we'll drop OFFRTG since it's less correlated than NETRTG

- We'll also drop Losses because it has a high chance of overfitting our model

FINAL VARIABLES TO DROP: These will be dropped in next iteration of the model, for now they'll stay in

- GP
- EFG%
- TS%
- PIE
- AST%
- OREB%
- DREB%
- OFFRTG

3.2 Training the model

In [6]:

```
X = dfold.drop(['W', 'Team', 'POSS', 'L', 'Wins', 'Losses', 'Team Achievement'], axis=1).values
y = dfold['W'].values

x_train,x_test,y_train,y_test = train_test_split(X,y,test_size=0.33,random_state=0)

lr = LinearRegression()
lr.fit(x_train, y_train)

y_pred = lr.predict(x_test)
print(f'predicted values: {y_pred}')

model = LinearRegression()
model = LinearRegression().fit(X, y)
```

```
predicted values: [ 14.68227465 105.92540309  46.9935854   89.60133269  70.0888045
  67.19255766  60.32195656  43.448111    26.58123721  68.77680274]
```

3.3 Evaluation of model

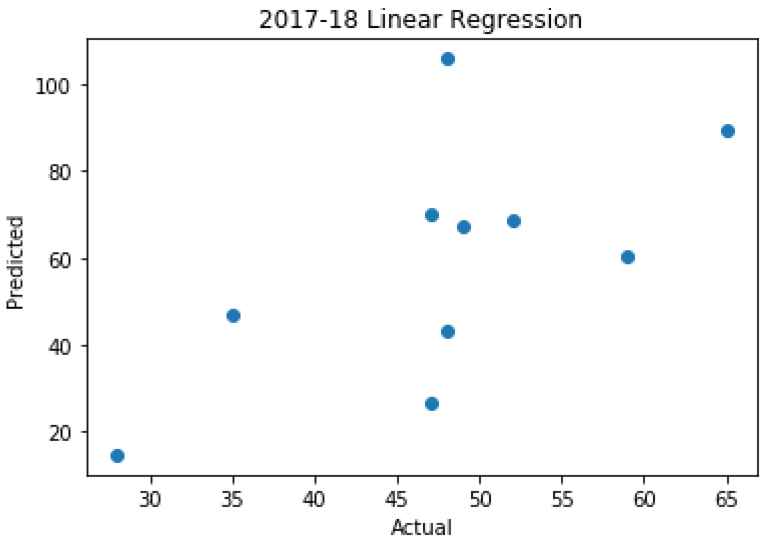
In [7]:

```
lr.fit(x_train, y_train)
print(f'r^2 of our model: {lr.score(x_test, y_test)}')
```

```
r^2 of our model: -4.880816045694511
```

In [8]:
```
plt.scatter(y_test,y_pred)
plt.title("2017-18 Linear Regression")
plt.xlabel('Actual')
plt.ylabel('Predicted')
```

Out[8]:
```
Text(0, 0.5, 'Predicted')
```



As can be seen from our plot above and r^2 value, our model is not yet very good. In the next model, we will remove some potential multicollinearity to improve the model's performance.

3.4 Predicted Wins

In [9]:

```
y_pred = ([math.floor(a) for a in y_pred])
```

In [10]:

```
pred_y_df = pd.DataFrame({'Actual Value': y_test, 'Predicted value': y_pred, 'Difference': y_test-y_pred})
pred_y_df

# will show us the predicted values for each team on our new data
```

Out[10]:

	Actual Value	Predicted value	Difference
0	28	14	14
1	48	105	-57
2	35	46	-11
3	65	89	-24
4	47	70	-23
5	49	67	-18
6	59	60	-1
7	48	43	5
8	47	26	21
9	52	68	-16

4 Second Model, less variables

As a refresher, we'll drop the following:

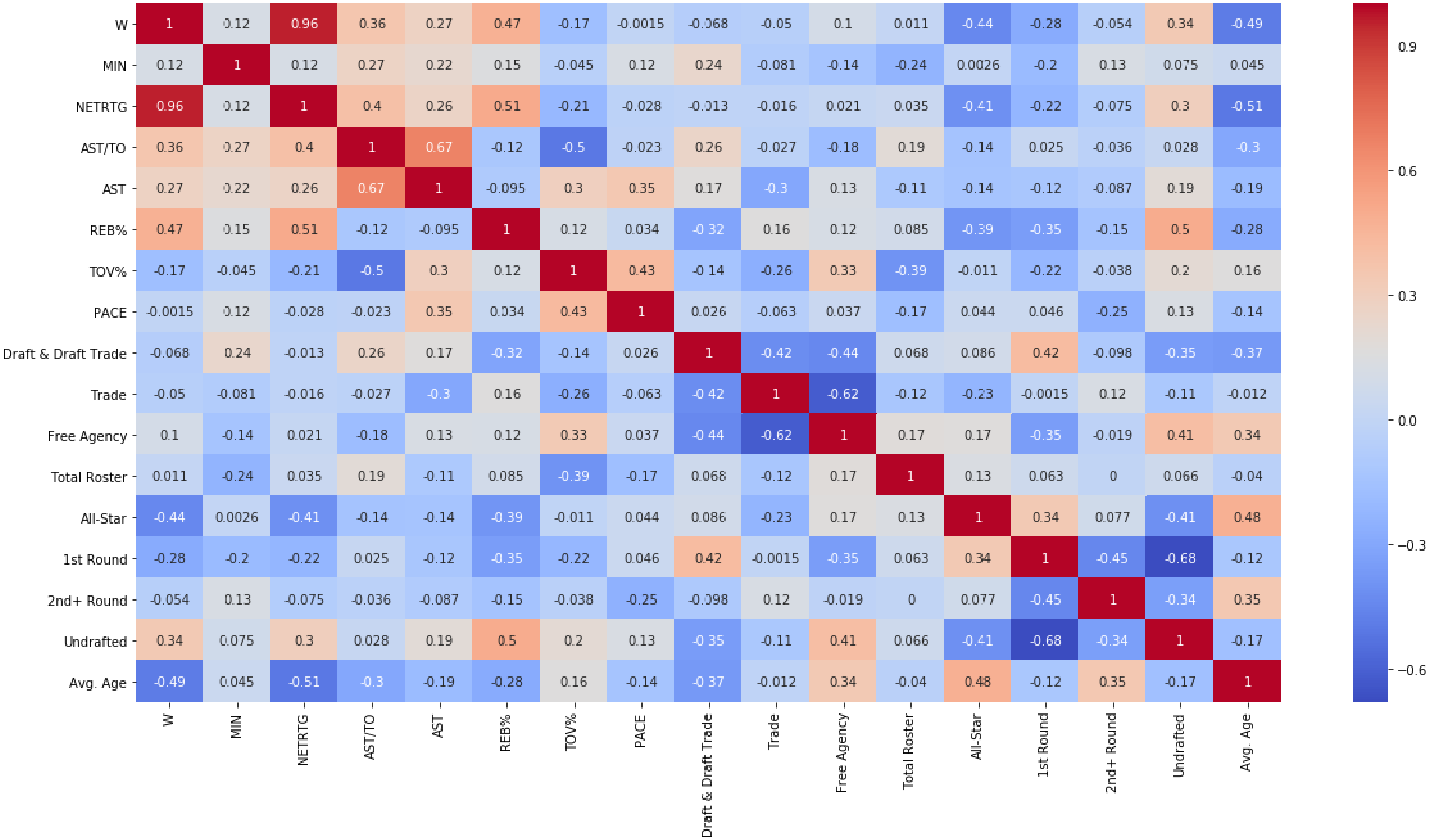
- GP
- EFG%
- TS%
- PIE

- AST%
- OREB%
- DREB%
- OFFRTG
- DEFRTG (highly negatively correlated)

4.1 Correlation Heatmap (new variables)

```
In [11]:  new_model_df = dfold.drop(['Team', 'POSS', 'L', 'Wins', 'Losses', 'GP',
                                  'EFG%', 'TS%', 'PIE', 'AST%', 'OREB%', 'DREB%', 'OFFRTG', 'DEFRTG'], axis=1)

           plt.subplots(figsize=(20,10))
           sns.heatmap(new_model_df.corr(), cmap= 'coolwarm', annot=True)
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1f2057d87b8>
```



4.1.1 Analysis of new correlation map (put in ppt)

My thought is that NETRTG is one of our strongest predictors as it's so highly correlated with wins (94%). REB% (62%), Free Agency Signings (46%), and Avg. Age (57%) should also play a large role.

4.2 Loading New Data

In [12]:

```
df1new = pd.read_csv('2020-21data1.csv')
df2new = pd.read_csv('2020-21data2.csv')
```

Data Cleaning

In [13]:

```
df1new = df1new.rename(columns={"TEAM": "Team"})
df1new['Team'] = df1new['Team'].replace(['LA Clippers'],'Los Angeles Clippers')
df2new['Team'] = df1new['Team'].replace(['Philadelphia Sixers'],'Philadelphia 76ers')
```

In [14]:

```
dfnew = pd.merge(df1new,df2new,on='Team', how='inner')
#df = df.drop('Unnamed: 20', axis=1)

# clean the same way as our old data
dfnew = dfnew.drop('MVP', axis=1)
dfnew = dfnew.sort_values('Team')
```

In [15]:

```
test = lr.predict(X)
print(test)
```

```
[ 24.          55.          14.68227465  36.          27.
  50.          24.          46.          39.          58.
  89.60133269  43.448111    42.          46.9935854   22.
  44.          44.          26.58123721  48.          29.
  48.          25.          68.77680274  21.          67.19255766
  27.          70.0888045   60.32195656 105.92540309  43.        ]
```

4.3 Training new model

In [16]:

```
X = dfold.drop(['Team', 'POSS', 'L', 'Wins', 'Losses', 'GP',
            'EFG%', 'TS%', 'PIE', 'AST%', 'OREB%', 'DREB%', 'OFFRTG', 'Team Achievement', 'DEFRTG'], axis=1)
y = dfold['W'].values

x_train,x_test,y_train,y_test = train_test_split(X,y,test_size=0.33,random_state=0)

lr = LinearRegression()
lr.fit(x_train, y_train)

y_pred = lr.predict(x_test)
print(f'predicted values: {y_pred}')

model = LinearRegression()
#model.fit(X, y) # idk if i need this too yet
model = LinearRegression().fit(X, y)
```

```
predicted values: [28. 48. 35. 65. 47. 49. 59. 48. 47. 52.]
```

4.4 Evaluation of Model

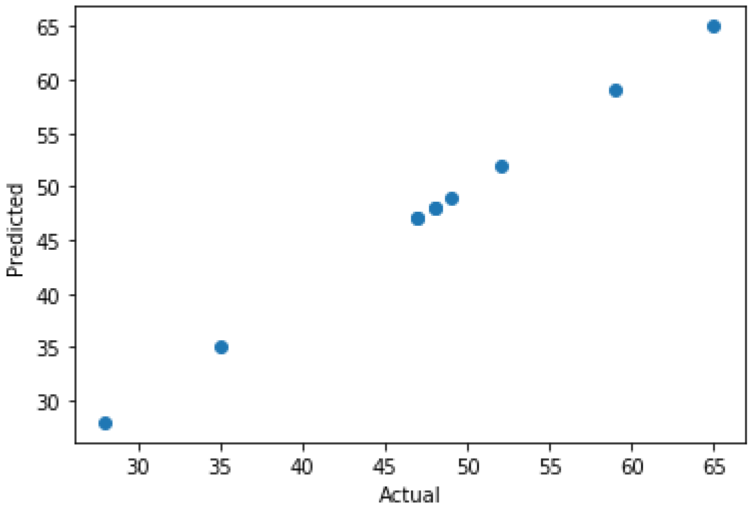
In [17]:

```
lr.fit(x_train, y_train)
print(f'r^2 of our model: {lr.score(x_test, y_test)}') # r^2 of our model (why so high?? may be overfitting)
```

```
r^2 of our model: 1.0
```

In [18]:
```
plt.scatter(y_test,y_pred)
plt.xlabel('Actual')
plt.ylabel('Predicted')
```

Out[18]:
```
Text(0, 0.5, 'Predicted')
```



4.5 Predicted Wins

In [19]:

```
y_pred = ([math.floor(a) for a in y_pred])
```

In [20]:

```
pred_y_df = pd.DataFrame({'Actual Value': y_test, 'Predicted value': y_pred, 'Difference': y_test-y_pred})
pred_y_df
```

Out[20]:

	Actual Value	Predicted value	Difference
0	28	28	0
1	48	48	0
2	35	35	0
3	65	65	0
4	47	47	0
5	49	49	0
6	59	59	0
7	48	48	0
8	47	47	0
9	52	52	0

4.6 Predicting 2020-21 Wins

In [21]:

```
X = dfold.drop(['Team', 'POSS', 'L', 'Wins', 'Losses', 'GP',
            'EFG%', 'TS%', 'PIE', 'AST%', 'OREB%', 'DREB%', 'OFFRTG', 'Team Achievement', 'DEFRTG'], axis=1)
test = lr.predict(X)
```

In [22]:

```
dfnew['pred_wins'] = list(test) # add to dataframe
# these values will be off since we're now training on an 82 game season
```

In [25]:

```
dfnew =dfnew.drop(columns={'Unnamed: 13',
       'Unnamed: 14', 'Unnamed: 15', 'Unnamed: 16', 'Unnamed: 17',
       'Unnamed: 18'}) # not sure why these values are showing up, we'll just drop them as they aren't signi
```

In [26]:

```
dfnew.head() # final dataframe, contains predicted wins.
# This will be used for our simulation in Excel
```

Out[26]:

	Team	GP	W	L	MIN	OFFRTG	DEFRTG	NETRTG	AST%	AST/TO	...	Free Agency	Total Roster	Wins	Losses	All-Star	1st Round	2 Ro
9	Atlanta Hawks	63	34	29	3049	113.6	112.3	1.2	59.4	1.80	...	7	15	43	21	1	10	
12	Boston Celtics	63	33	30	3039	112.8	111.3	1.5	56.3	1.63	...	4	15	34	29	0	12	
3	Brooklyn Nets	62	42	20	3001	117.3	113.0	4.2	62.2	1.95	...	5	15	21	41	0	6	
17	Charlotte Hornets	62	30	32	2986	110.4	111.8	-1.4	67.3	1.78	...	5	14	28	34	0	7	
21	Chicago Bulls	62	26	36	2996	110.6	112.2	-1.6	63.6	1.74	...	4	14	31	31	0	7	

5 rows × 33 columns

In [77]:

```
dfnew.to_csv('out.csv', index=False) # output to csv, next part will be in excel
```