Predicting 2022 NBA All Stars

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Introduction

There are 30 **National Basektball Association** (NBA) teams. Those 30 teams are split into two conferences, Eastern and Western, and there are 15 players on each roster which obviously means there is a total of 450 players in the NBA. 82 regular season games are played by each team over the course of 6 months usually from late October to mid-April. During the course of a long season, the players do get a mid-season break. This break is known as the All-Star Break where *some* players get a break from Friday to the next Wednesday. During this All-Star Break, there is an 3 day event called NBA All-Star weekend which lasts from Friday to Sunday. The 3 day event is headlined by the All-Star Game, which is held on Sunday. Out the 450 players in the NBA, there are 24 players selected to play in the All-Star Game, 12 from each conference. The player selection process begins with fan voting, which is worth 50%, player voting worth 25%, and basketball media picking the starting 5 for each conference. The remaining 14 players are selected by the NBA coaches. Then the two leading vote getters are designated team captains and will then choose their respective teams.

Relevance

Every year, there is controversy selecting the NBA All-Stars. For example, in 2017 fringe(and nowhere near the All-Star level) Golden State Warriors Center Zaza Pachulia was nearly voted into the NBA All-Star game due to weight of the fan vote(80% at the time) and because the Warriors were the most popular team in the league at the time. In order to reduce bias, we think there should be an unbiased selective process for the All-Stars in order to reduce controversy. Analytics have become extremely prevalent in sports and in basketball it makes sense there is an analyltical way of selecting the All-Stars.

How the project works

In the project, we start by scraping Basketball Reference data. This data includes the basic and advanced statistics of NBA players over the past ten years. Then we scraped the All-Stars of the past ten years. After scraping all the data, we use a correlation matrix to determine which statistics were the most important in becoming an All-Star and we build our predictive model using those statistics. Finally, we use logistic regression to better understand the relationship between the different variables by estimating probabilities. This type of analysis allows us to predict the liklihood of an event, which in our case is the 2022 NBA All Stars.

In [2]:
```
#!pip install lxml
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import math
import sqlite3
import scipy.stats as stats
import requests
import sklearn
from bs4 import BeautifulSoup, SoupStrainer
from datetime import timedelta, datetime
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from urllib.request import urlopen
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import RFE, SelectFromModel, SelectKBest
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import make_pipeline
from sklearn.base import clone
from sklearn.metrics import accuracy_score, brier_score_loss
from sklearn.model_selection import train_test_split
import sys, os
```

This function scrapes data for All-Stars in any given year.

In [3]:
```
def scrape_all_stars(year):

    url = f'https://www.basketball-reference.com/allstar/NBA_{year}.html'
    html = urlopen(url)

    soup = BeautifulSoup(html, features = "lxml")

    rows = soup.findAll('tr')[6:]
    rows_data = [[td.getText() for td in rows[i].findAll('th')]
                        for i in range(len(rows))]

    arr = []
    for i in rows_data:
        if ((len(i) == 1) and (i[0] != 'Team Totals')):
            arr.append(i)

    df = pd.DataFrame(arr)

    df.columns= ["Player"]
    df["Year"] = year
    df["Player"] = pd.Series(df["Player"],dtype = "string")

    return df
```

This function scrapes Basketball Reference for basic stats in any given year.

In [4]:

```
def scrape_basic_stats(year):
    url = f"https://www.basketball-reference.com/leagues/NBA_{year}_per_gam
    html = urlopen(url)

    soup = BeautifulSoup(html, features = "lxml")

    headers = [th.getText() for th in soup.findAll('tr', limit=2)[1].findAl

    rows = soup.findAll('tr')[0:]
    rows_data = [[td.getText() for td in rows[i].findAll('td')]
                        for i in range(len(rows))]

    df = pd.DataFrame(rows_data)
    #df = df.drop(columns=[28])
    df.columns = ["Player", "Pos", "Age", "Tm", "G", "GS", "MP", "FG", "FGA
    df = df.dropna()

    df["Year"] = year
    pd.set_option("display.max_rows", 729, "display.max_columns", 30)

    df["Is All Star"] = 0

    df = df.drop_duplicates(subset=['Player'])
    df = df.reset_index()
    df = df.drop(columns = ["index"])

    y = df["Year"]
    p = df["Player"]

    for i in range(0, len(df.index)):
        if(year != 2022):
            if (p[i] in scrape_all_stars(y[i])["Player"].unique()):
                df.at[i, 'Is All Star'] = 1



    return df
```

This function scrapes Basketball Reference for advanced stats in any given year.

In [5]:
```
def scrape_advanced_stats(year):
    url = f'https://www.basketball-reference.com/leagues/NBA_{year}_advance
    html = urlopen(url)

    soup = BeautifulSoup(html, features = "lxml")

    headers = [th.getText() for th in soup.findAll('tr', limit=2)[1].findAl

    rows = soup.findAll('tr')[0:]
    rows_data = [[td.getText() for td in rows[i].findAll('td')]
                        for i in range(len(rows))]

    df = pd.DataFrame(rows_data)

    df = df.drop(columns=[18, 23])
    df.columns = ["Player", "Pos", "Age", "Tm", "G", "MP", "PER", "TS%", "3

    df = df.drop_duplicates(subset=['Player'])
    df = df.drop(columns=["Player", "Pos", "Age", "Tm", "G", "MP"])

    df = df.dropna()
    df = df.reset_index()
    df = df.drop(columns = ["index"])

    return df
```

In this function we will scrape all data for the All Stars of the previous 10 years and merge them into one dataframe.

In [7]:

```
years = [2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021]
arr = []
arr2 = []
arr3 = []
df_arr = []
final_df = []

for y in years:
    arr2.append(scrape_all_stars(y))
    arr.append(scrape_advanced_stats(y))
    arr3.append(scrape_basic_stats(y))

for i in range(0, len(years)):
    df_arr.append(pd.concat([arr3[i],arr[i]], axis = 1))

for i in range(0, len(years)):
    final_df.append(df_arr[i])

df = final_df[0]
for i in range (1, len(years)):
    df = pd.concat([final_df[i],df])

df = df.reset_index()
df = df.drop(columns = "index")
#pd.set_option("display.max_rows", 729, "display.max_columns", 50)
df
```

Out[7]:

	Player	Pos	Age	Tm	G	GS	MP	FG	FGA	FG%	3P	3PA	3P%	2P	2PA	...	DRI
0	Precious Achiuwa	PF	21	MIA	61	4	12.1	2.0	3.7	.544	0.0	0.0	.000	2.0	3.7	...	2
1	Jaylen Adams	PG	24	MIL	7	0	2.6	0.1	1.1	.125	0.0	0.3	.000	0.1	0.9	...	1
2	Steven Adams	C	27	NOP	58	58	27.7	3.3	5.3	.614	0.0	0.1	.000	3.3	5.3	...	2
3	Bam Adebayo	C	23	MIA	64	64	33.5	7.1	12.5	.570	0.0	0.1	.250	7.1	12.4	...	2
4	LaMarcus Aldridge	C	35	TOT	26	23	25.9	5.4	11.4	.473	1.2	3.1	.388	4.2	8.3	...	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
5015	Chris Wright	SF	23	GSW	24	1	7.8	1.0	1.9	.511	0.0	0.0		1.0	1.9	...	1
5016	Dorell	SF	26	GSW	61	61	27.0	3.6	8.6	.422	1.7	4.8	.360	1.9	3.8	...	1

In [12]:

```
temp_df = df
```

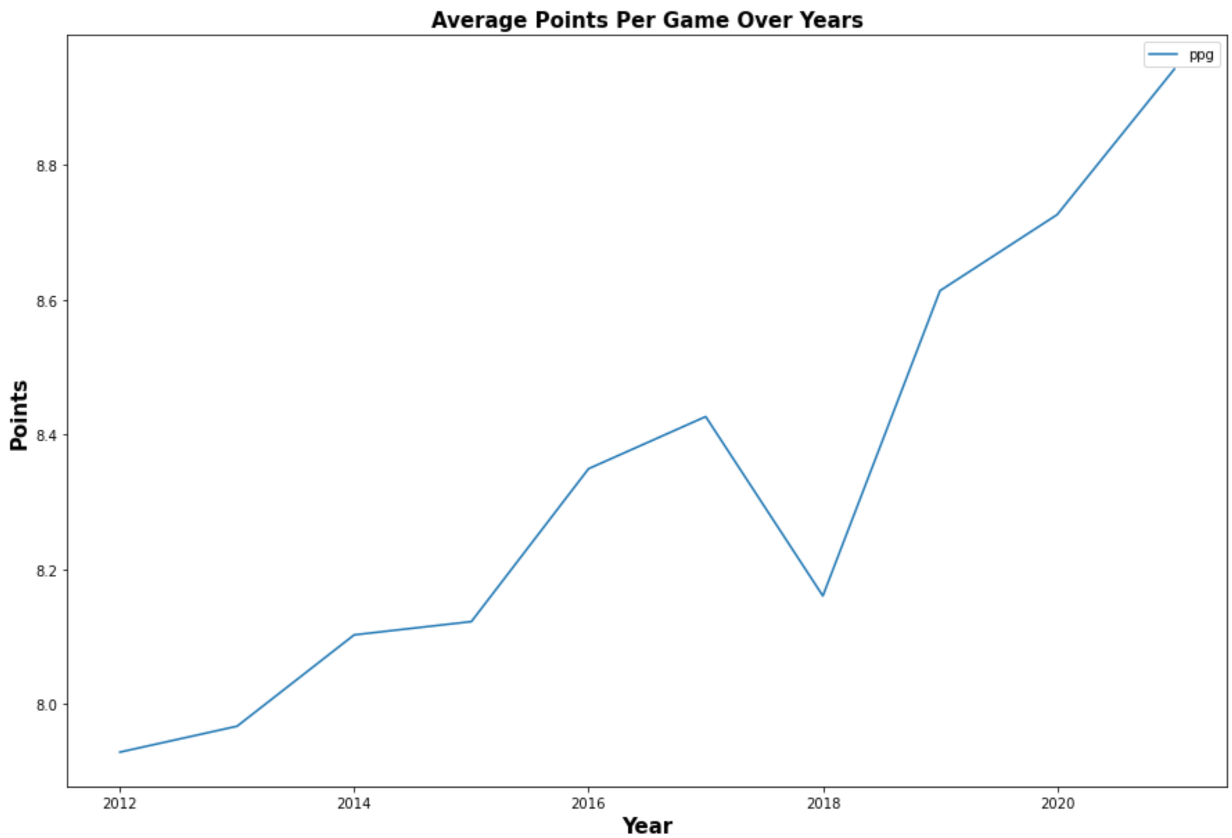
Data Analysis

We use this function to find the average of some of the most important statistics in a given All-Star team.

In [13]:
```
def stat_avg (col_name):
    arr = []
    for i in range (0, len(years)):
        newdf = final_df[i]
        newdf[col_name] = newdf[col_name].astype(float)
        arr.append(newdf[col_name].mean())

    return arr
```

In [14]:
```
# In this function we will plot the PPG for all stars of the last 10 years
# Find the mean PPG over the last 10 years and graph as line graph


l = pd.DataFrame({'ppg': stat_avg("PTS")},
                 index=years)
lines = l.plot.line(figsize=(15, 10))

plt.xlabel("Year", size = 15, weight = 'bold')
plt.ylabel("Points", size = 15, weight = 'bold')

plt.title("Average Points Per Game Over Years", size = 15, weight = 'bold')
```

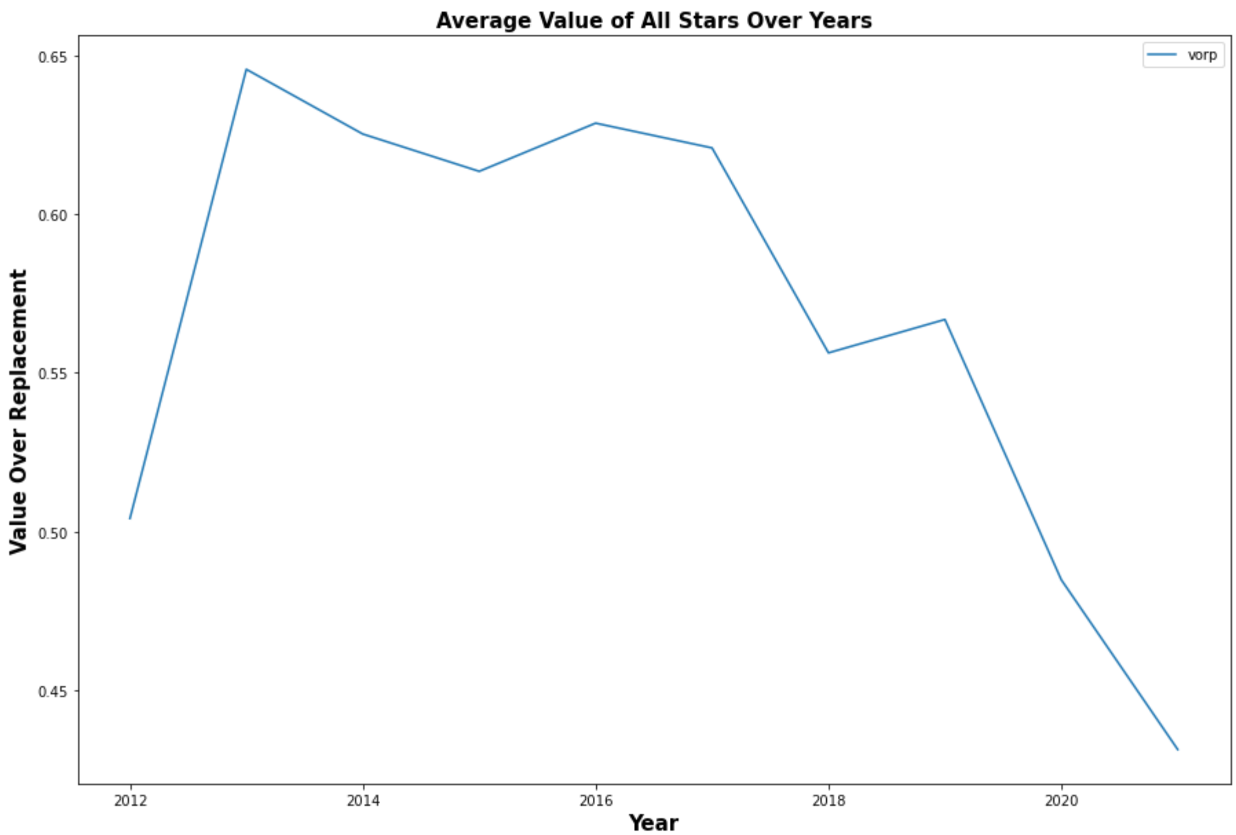
Out[14]:
```
Text(0.5, 1.0, 'Average Points Per Game Over Years')
```



From what we can see in the Average Points Per Game Over Years, their is an upward trend for average points per game over the years.

In [15]:
```
# In this function we will plot the VORP for all stars of the last 10 years

l = pd.DataFrame({'vorp': stat_avg("VORP")},
                 index=years)
lines = l.plot.line(figsize=(15, 10))

plt.xlabel("Year", size = 15, weight = 'bold')
plt.ylabel("Value Over Replacement", size = 15, weight = 'bold')

plt.title("Average Value of All Stars Over Years", size = 15, weight = 'bol
```

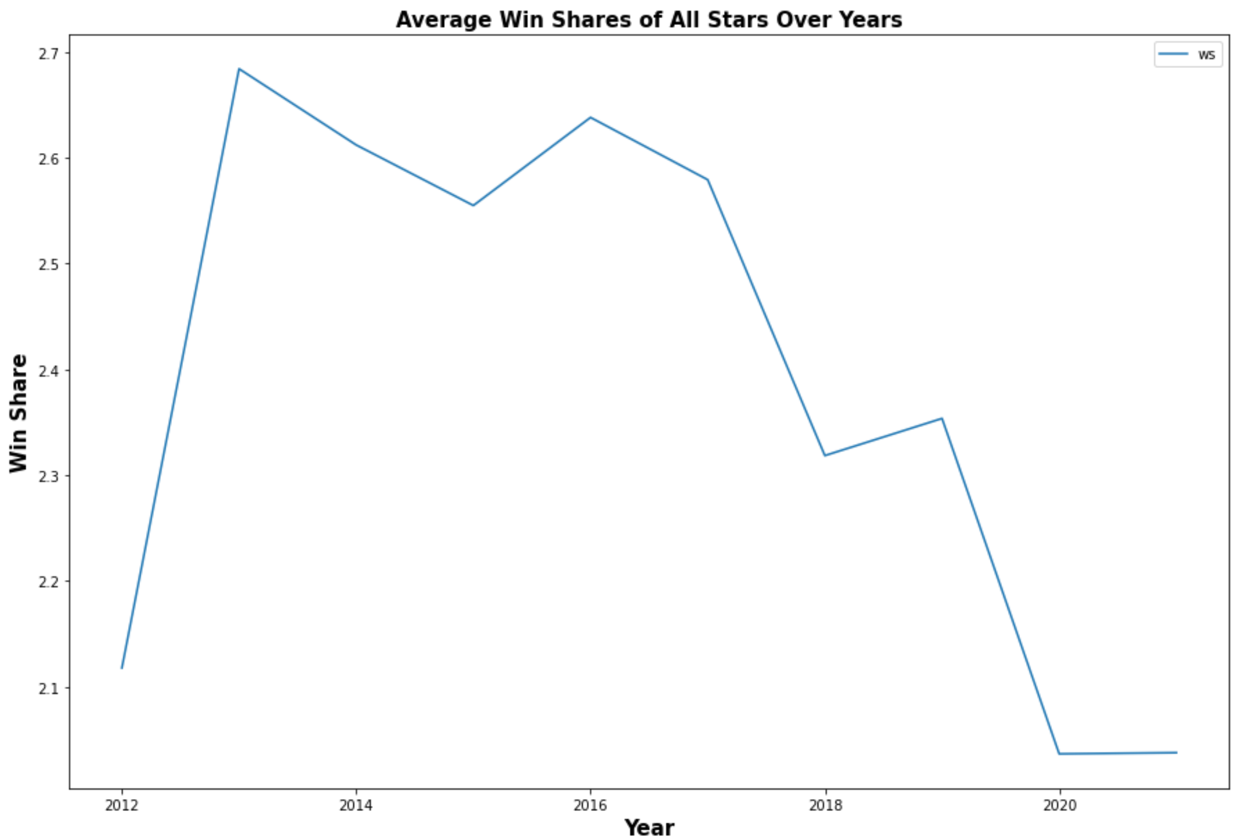
Out[15]:
```
Text(0.5, 1.0, 'Average Value of All Stars Over Years')
```



From what we can see in Average Player Efficient Rating of All Stars Over, the Per has increaswed over the pas few years with a slight spike in 2017, and still in on a rise.

In [16]:
```
# In this function we will plot the WS for all stars of the last 10 years
l = pd.DataFrame({'ws': stat_avg("WS")},
                 index=years)
lines = l.plot.line(figsize=(15, 10))

plt.xlabel("Year", size = 15, weight = 'bold')
plt.ylabel("Win Share", size = 15, weight = 'bold')

plt.title("Average Win Shares of All Stars Over Years", size = 15, weight =
```

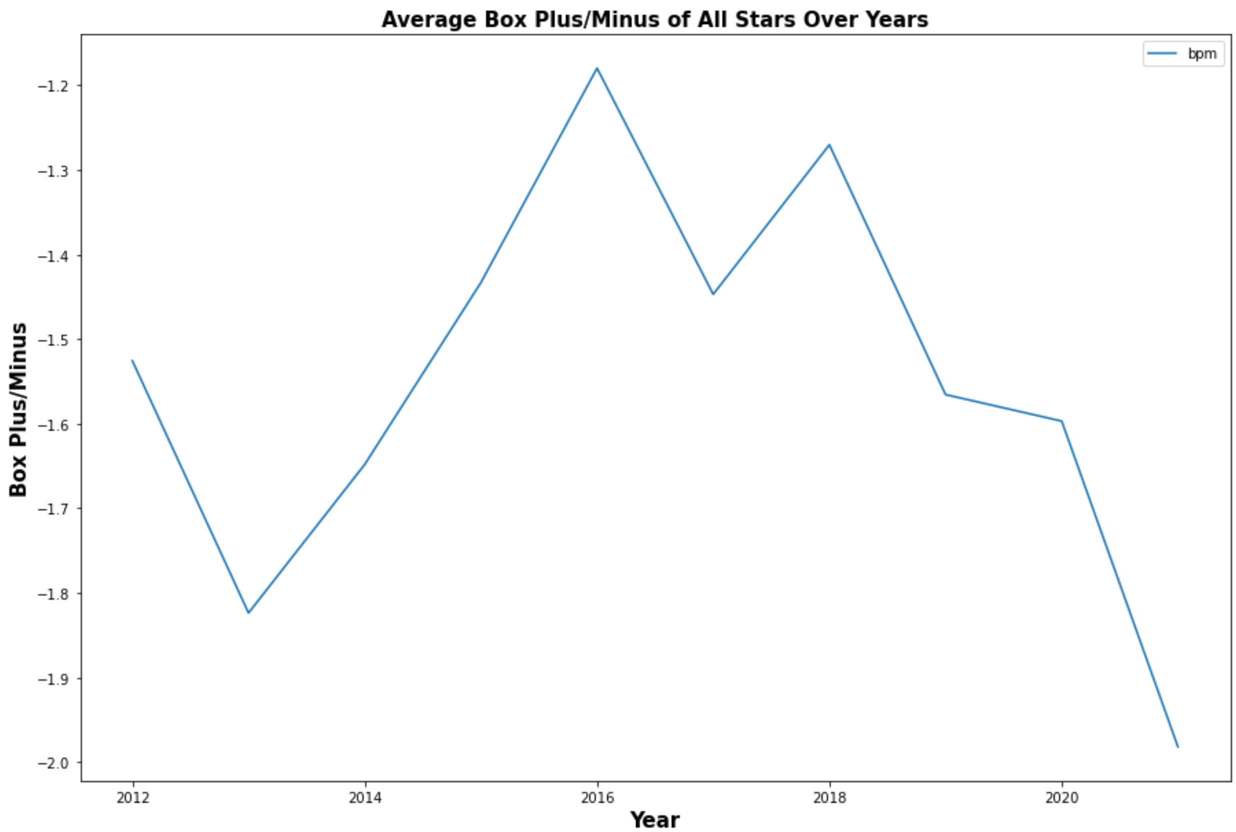
Out[16]:
```
Text(0.5, 1.0, 'Average Win Shares of All Stars Over Years')
```



Regarding the Average Win Shares, from 2012 it goes on a steady rise, plateau around 2015, rrises again and steadily drrops till 2020. The drop could be attributed to the lack of games played in the 2021 dataframe.

In [17]:
```
# In this function we will plot the BPM for all stars of the last 10 years
l = pd.DataFrame({'bpm': stat_avg("BPM")},
              index=years)
lines = l.plot.line(figsize=(15, 10))

plt.xlabel("Year", size = 15, weight = 'bold')
plt.ylabel("Box Plus/Minus", size = 15, weight = 'bold')

plt.title("Average Box Plus/Minus of All Stars Over Years", size = 15, weig
```

Out[17]:
```
Text(0.5, 1.0, 'Average Box Plus/Minus of All Stars Over Years')
```

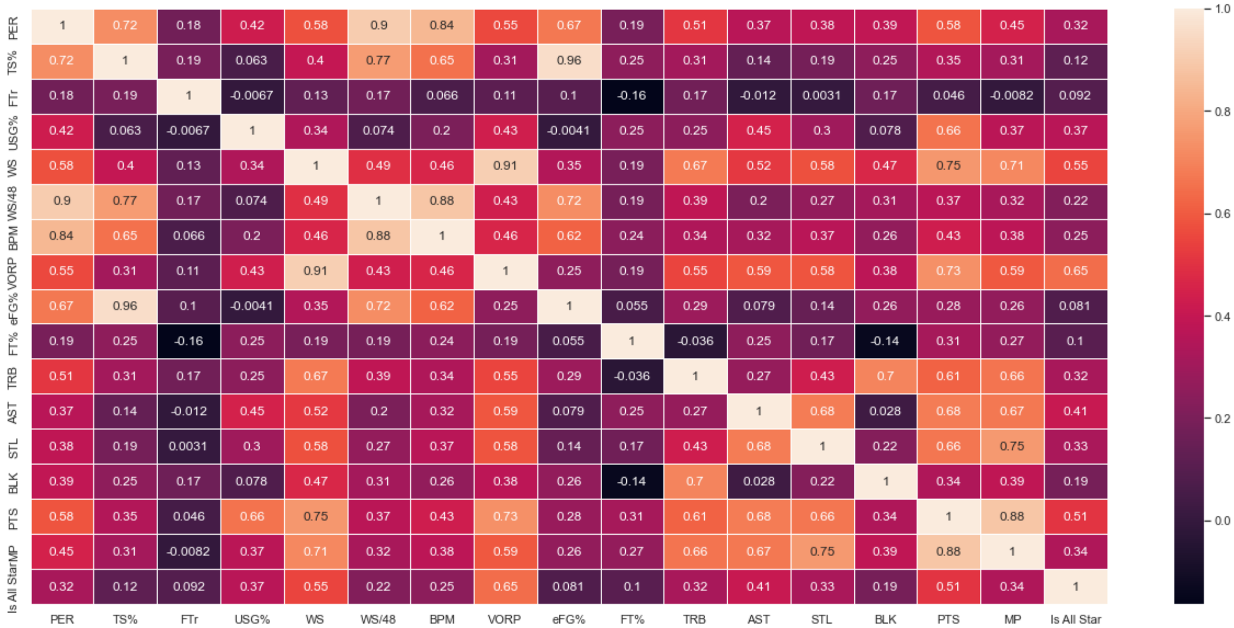


Regarding the Average Box Plus/Minus score over the years there is an upward trend from 2013 after a decline from 2012 for box plus/minus over the years.

In [18]:
```
all_star = df[df['Is All Star']==1]
not_all_star = df[df['Is All Star']==0]
```

In [19]:
```
# visualise correlation matrix

temp_df = df
temp_df = temp_df.replace('', 0.0,regex=True)

df["PER"] = pd.to_numeric(df["PER"], downcast="float")
df["TS%"] = pd.to_numeric(df["TS%"], downcast="float")
df["FTr"] = pd.to_numeric(df["FTr"], downcast="float")
df["USG%"] = pd.to_numeric(df["USG%"], downcast="float")
df["WS"] = pd.to_numeric(df["WS"], downcast="float")
df["WS/48"] = pd.to_numeric(df["WS/48"], downcast="float")
df["BPM"] = pd.to_numeric(df["BPM"], downcast="float")
df["VORP"] = pd.to_numeric(df["VORP"], downcast="float")
df["eFG%"] = pd.to_numeric(df["eFG%"], downcast="float")
df["FT%"] = pd.to_numeric(df["FT%"], downcast="float")
df["TRB"] = pd.to_numeric(df["TRB"], downcast="float")
df["AST"] = pd.to_numeric(df["AST"], downcast="float")
df["STL"] = pd.to_numeric(df["STL"], downcast="float")
df["BLK"] = pd.to_numeric(df["BLK"], downcast="float")
df["PTS"] = pd.to_numeric(df["PTS"], downcast="float")
df["MP"] = pd.to_numeric(df["MP"], downcast="float")
df["Is All Star"] = pd.to_numeric(df["Is All Star"], downcast="float")



data = {'PER': df['PER'],
        'TS%': df['TS%'],
        'FTr': df['FTr'],
        'USG%': df['USG%'],
        'WS': df['WS'],
        'WS/48': df['WS/48'],
        'BPM': df['BPM'],
        'VORP': df['VORP'],
        'eFG%': df['eFG%'],
        'FT%': df['FT%'],
        'TRB': df['TRB'],
        'AST': df['AST'],
        'STL': df['STL'],
        'BLK': df['BLK'],
        'PTS': df['PTS'],
        'MP': df['MP'],
        'Is All Star' : df['Is All Star']

        }

df = pd.DataFrame(data, columns=['PER','TS%', 'FTr', 'USG%', 'WS','WS/48','


corrMatrix = df.corr()
sns.set(rc = {'figure.figsize':(22,10)})
sns.heatmap(corrMatrix, annot=True, linewidths=.5)
```

Out[19]: <AxesSubplot:>



From our correlation matrix, we can see that WS/48, BPM, VORP, and TS% are the most important statistics for our prediction model.

In [20]:
```
temp_df["PER"] = pd.to_numeric(temp_df["PER"], downcast="float")
temp_df["TS%"] = pd.to_numeric(temp_df["TS%"], downcast="float")
temp_df["FTr"] = pd.to_numeric(temp_df["FTr"], downcast="float")
temp_df["USG%"] = pd.to_numeric(temp_df["USG%"], downcast="float")
temp_df["WS"] = pd.to_numeric(temp_df["WS"], downcast="float")
temp_df["WS/48"] = pd.to_numeric(temp_df["WS/48"], downcast="float")
temp_df["BPM"] = pd.to_numeric(temp_df["BPM"], downcast="float")
temp_df["VORP"] = pd.to_numeric(temp_df["VORP"], downcast="float")
temp_df["eFG%"] = pd.to_numeric(temp_df["eFG%"], downcast="float")
temp_df["FT%"] = pd.to_numeric(temp_df["FT%"], downcast="float")
temp_df["TRB"] = pd.to_numeric(temp_df["TRB"], downcast="float")
temp_df["AST"] = pd.to_numeric(temp_df["AST"], downcast="float")
temp_df["STL"] = pd.to_numeric(temp_df["STL"], downcast="float")
temp_df["BLK"] = pd.to_numeric(temp_df["BLK"], downcast="float")
temp_df["PTS"] = pd.to_numeric(temp_df["PTS"], downcast="float")
temp_df["MP"] = pd.to_numeric(temp_df["MP"], downcast="float")
```

Model Building

We will know write a function that shows us the most important statistics after testing each of our models. We use scikit-learn's brier_score_loss as that type of loss helps us predict players with the highest probabilities of making the 2022 All-Star Game.

In [21]:
```
def model_builder(model, stats):
    train_acc = accuracy_score(model.predict(X_train[stats]), y_train)
    val_acc = accuracy_score(model.predict(X_val[stats]), y_val)

    t_loss = brier_score_loss(y_train, model.predict_proba(X_train[stats])[
    v_loss = brier_score_loss(y_val, model.predict_proba(X_val[stats])[:, 1

    print('\nTraining Accuracy: ' + str(train_acc),' Training Loss: '+ str(
    print('\nValidation Accuracy: '+str(val_acc), 'Validation Loss: '+str(v
```

In [33]:
```
all_star_train, all_star_valid = sklearn.model_selection.train_test_split(a
non_all_star_train, non_all_star_valid = sklearn.model_selection.train_test

training = pd.concat([all_star_train, non_all_star_train], ignore_index=Tru
validity = pd.concat([all_star_valid, non_all_star_valid], ignore_index=Tru

test = temp_df[(temp_df.Year > 2020)]
training = training.replace('', 0.0)
validity = validity.replace('', 0.0)
```

Hypothesis Test

In [34]:
```
stats = ['PER','TS%', 'FTr', 'USG%', 'WS','WS/48','BPM','VORP','eFG%','FT%'

X_train = training[stats]
y_train = training["Is All Star"]

X_val = validity[stats]
y_val = validity["Is All Star"]
X_train = X_train.fillna(0.0)

X_train["PER"] = pd.to_numeric(X_train["PER"], downcast="float")
X_train["TS%"] = pd.to_numeric(X_train["TS%"], downcast="float")
X_train["FTr"] = pd.to_numeric(X_train["FTr"], downcast="float")
X_train["USG%"] = pd.to_numeric(X_train["USG%"], downcast="float")
X_train["WS"] = pd.to_numeric(X_train["WS"], downcast="float")
X_train["WS/48"] = pd.to_numeric(X_train["WS/48"], downcast="float")
X_train["BPM"] = pd.to_numeric(X_train["BPM"], downcast="float")
X_train["VORP"] = pd.to_numeric(X_train["VORP"], downcast="float")
X_train["eFG%"] = pd.to_numeric(X_train["eFG%"], downcast="float")
X_train["FT%"] = pd.to_numeric(X_train["FT%"], downcast="float")
X_train["TRB"] = pd.to_numeric(X_train["TRB"], downcast="float")
X_train["AST"] = pd.to_numeric(X_train["AST"], downcast="float")
X_train["STL"] = pd.to_numeric(X_train["STL"], downcast="float")
X_train["BLK"] = pd.to_numeric(X_train["BLK"], downcast="float")
X_train["PTS"] = pd.to_numeric(X_train["PTS"], downcast="float")
X_train["MP"] = pd.to_numeric(X_train["MP"], downcast="float")
```

In [35]:
```
min_loss = 1
selector_best = None


for i in range(1, len(stats)):
    selector = RFE(estimator = LogisticRegression(max_iter=150), n_features

    rfe_pipe = make_pipeline(StandardScaler(), selector)

    rfe_pipe.fit(X_train[stats], y_train)
    loss = brier_score_loss(y_val, rfe_pipe.predict_proba(X_val)[:, 1])

    if loss < min_loss:
        min_loss = loss
        selector_best = clone(selector)

rfe_pipe = make_pipeline(StandardScaler(), selector_best)

rfe_pipe.fit(X_train, y_train)
rfe_support = selector_best.get_support()
rfe_features = X_train.loc[:, rfe_support].columns

print(str(len(rfe_features)), 'best features according to RFE:')
print(rfe_features.tolist())
model_builder(rfe_pipe, stats)
```

```
13 best features according to RFE:
['PER', 'TS%', 'USG%', 'WS', 'WS/48', 'VORP', 'eFG%', 'FT%', 'TRB', 'AS
T', 'BLK', 'PTS', 'MP']

Training Accuracy: 0.9768832204065365  Training Loss: 0.017010862131027676

Validation Accuracy: 0.9765033851055357 Validation Loss: 0.01652568989368994
```

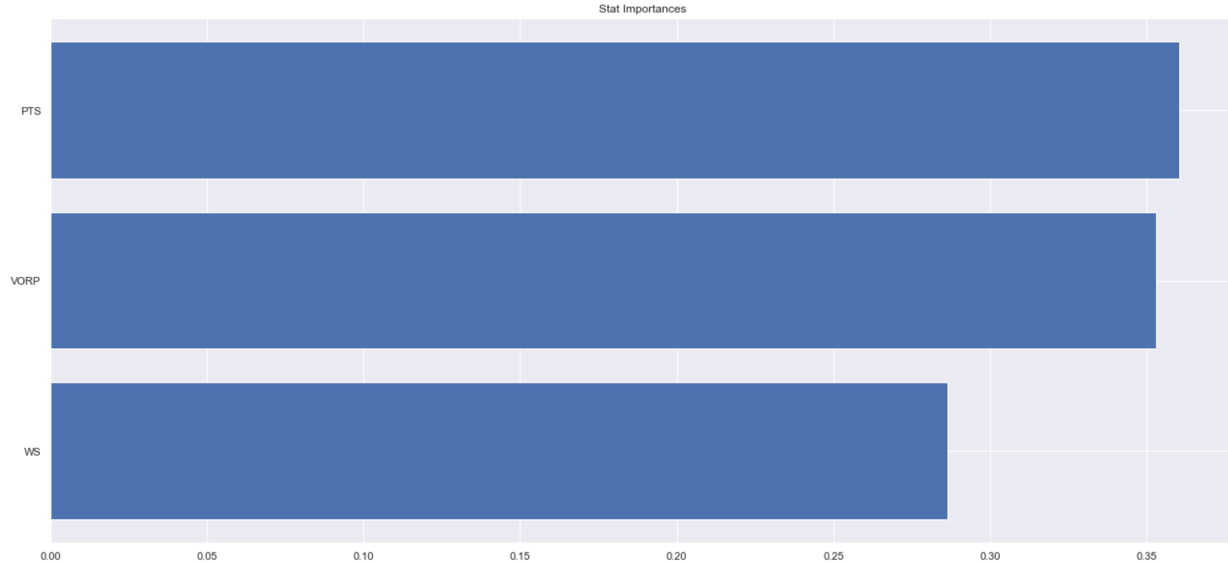
In [36]:
```
log_reg = LogisticRegression()
logreg_pipe = make_pipeline(StandardScaler(), log_reg)
logreg_pipe.fit(X_train[rfe_features], y_train)

pd.DataFrame({"Coefs": log_reg.coef_.reshape((-1))}, index=rfe_features)
```

Out[36]:

	Coefs
PER	-1.495861
TS%	-0.471586
USG%	1.015962
WS	0.868906
WS/48	1.049721
VORP	0.261917
eFG%	0.095416
FT%	0.218654
TRB	0.604788
AST	0.508561
BLK	0.187649
PTS	0.668209
MP	1.138225

In [37]:
```
min_loss = 1
selector_best = None

for i in range(1, len(stats)):
    rf = RandomForestClassifier(max_depth=7,
                                random_state=7, oob_score=False)

    rf_selector = SelectFromModel(rf, max_features=i)
    rf_selector.fit(X_train, y_train)

    rf_support = rf_selector.get_support()
    rf_features = X_train.loc[:, rf_support].columns

    rf.fit(X_train[rf_features], y_train)

    loss = brier_score_loss(y_val, rf.predict_proba(X_val[rf_features])[:,

    if loss < min_loss:
        min_loss = loss
        best_features = rf_features


rf_features = best_features
rf.fit(X_train[rf_features], y_train)

print(str(len(rf_features)), 'best features according to SelectFromModel:')
print(rf_features.tolist())
model_builder(rf, rf_features)

index = np.argsort(rf.feature_importances_)
features = X_train.columns[index]
plt.barh(width=rf.feature_importances_[index], y=best_features);
plt.title("Stat Importances");
```

```
3 best features according to SelectFromModel:
['WS', 'VORP', 'PTS']

Training Accuracy: 0.9912315663611  Training Loss: 0.008357353307714033

Validation Accuracy: 0.9757068896853843 Validation Loss: 0.01699792003194
744
```


Stat Importances
PTS
VORP
WS
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35

In [38]:
```
X_test = test[features]
y_test = test["Is All Star"].astype(int)

def test_model(model, features):
    proba = model.predict_proba(test[features])[:, 1]
    pred = (proba > 0.65).astype(int)

    acc = accuracy_score(y_test, pred)
    loss = brier_score_loss(y_test, proba)

    return proba, pred

df = training.append(validity, ignore_index = True)

X, y = df.drop("Is All Star", axis=1), df["Is All Star"]

logreg_pipe.fit(X[rfe_features], y);
rf.fit(X[rf_features], y);

logreg_test = test_model(logreg_pipe, rfe_features)
rf_test = test_model(rf, best_features)

print("Logistic Regression Model: \n", sep="")
test_probability_lr = logreg_test[0]
test_prediction_lr = test_probability_lr > 0.65

acc_logreg = accuracy_score(y_test, test_prediction_lr)
loss_logreg = brier_score_loss(y_test, test_probability_lr)

print('Accuracy: \n'+str(acc_logreg)+ '\n Loss: \n'+str(loss_logreg))

print("\nRandom Forest Classifier: \n", sep="")
test_probability_rf = rf_test[0]
test_prediction_rf = test_probability_rf > 0.65

acc_rf = accuracy_score(y_test, test_prediction_rf)
loss_rf = brier_score_loss(y_test, test_probability_rf)

print('Accuracy: \n'+str(acc_rf)+ '\n Loss: \n'+str(loss_rf))
```

```
Logistic Regression Model:

Accuracy:
0.9777777777777777
 Loss:
0.013543659792650629

Random Forest Classifier:

Accuracy:
0.9888888888888889
 Loss:
0.00719861314302389
```

Logistic Regression

In [39]:
```
basic2022 =  scrape_basic_stats(2022)
advanced2022 = scrape_advanced_stats(2022)

final2022 = pd.concat([basic2022,advanced2022], axis = 1)
```

In [40]:
```

y_pred_proba = []

for i in enumerate(logreg_test[0]):
    y_pred_proba.append(i[1])
y_pred_proba = np.asarray(y_pred_proba)

results_all_star = pd.DataFrame({
    "Player": test["Player"],
    "all_star_probability": y_pred_proba
    })

all_star_chances = test[['Player', 'Year']]
all_star_results = results_all_star.merge(all_star_chances, on='Player').so
```

In [41]:
```
all_star_results.head(24)
```

Out[41]:

	Player	all_star_probability	Year
262	Nikola Jokić	0.997528	2021
11	Giannis Antetokounmpo	0.967343	2021
129	Luka Dončić	0.967121	2021
115	Stephen Curry	0.945080	2021
296	Damian Lillard	0.931932	2021
420	Julius Randle	0.900711	2021
145	Joel Embiid	0.861287	2021
200	James Harden	0.858381	2021
516	Russell Westbrook	0.804602	2021
537	Trae Young	0.765062	2021
251	LeBron James	0.755618	2021
243	Kyrie Irving	0.710588	2021
347	Donovan Mitchell	0.696864	2021
472	Jayson Tatum	0.687562	2021
292	Kawhi Leonard	0.678708	2021
37	Bradley Beal	0.650642	2021
503	Nikola Vučević	0.606729	2021
83	Jimmy Butler	0.605388	2021
443	Domantas Sabonis	0.565864	2021
527	Zion Williamson	0.556991	2021
285	Zach LaVine	0.548656	2021
3	Bam Adebayo	0.474473	2021
490	Karl-Anthony Towns	0.446257	2021
139	Kevin Durant	0.439782	2021

Conclusion

In conclusion, we scraped data from basketball reference and stored it in several dataframes. We then were able to use a correlation matrix to determine which statistics were the most important in becoming an All-Star. After plotting out heat map we came to the conclusion that WS/48, BPM, VORP, and TS% are the most important statistics. With this information we created our predictive model and then performed logistic regression based on the validation model. We were able to predict all stars for 2022 with a high accuracy. Obviously it is imposssible to create a model that can predict the 2022 All-Star team with 100% accuracy due to factors such as fan voting.

Glossary

PER - Player Efficiency Rating (available since the 1951-52 season); PER is a rating developed by ESPN.com columnist John Hollinger. In John's words, "The PER sums up all a player's positive accomplishments, subtracts the negative accomplishments, and returns a per-minute rating of a player's performance." Please see the article Calculating PER for more information.

TS% - True Shooting Percentage; the formula is PTS / (2 * TSA). True shooting percentage is a measure of shooting efficiency that takes into account field goals, 3-point field goals, and free throws.

ORB% - Offensive Rebound Percentage (available since the 1970-71 season in the NBA); the formula is 100 * (ORB * (Tm MP / 5)) / (MP * (Tm ORB + Opp DRB)). Offensive rebound percentage is an estimate of the percentage of available offensive rebounds a player grabbed while he was on the floor.

DRB% - Defensive Rebound Percentage (available since the 1970-71 season in the NBA); the formula is 100 * (DRB * (Tm MP / 5)) / (MP * (Tm DRB + Opp ORB)). Defensive rebound percentage is an estimate of the percentage of available defensive rebounds a player grabbed while he was on the floor.

TRB% - Total Rebound Percentage (available since the 1970-71 season in the NBA); the formula is 100 * (TRB * (Tm MP / 5)) / (MP * (Tm TRB + Opp TRB)). Total rebound percentage is an estimate of the percentage of available rebounds a player grabbed while he was on the floor.

USG% - Usage Percentage (available since the 1977-78 season in the NBA); the formula is 100 * ((FGA + 0.44 * FTA + TOV) * (Tm MP / 5)) / (MP * (Tm FGA + 0.44 * Tm FTA + Tm TOV)). Usage percentage is an estimate of the percentage of team plays used by a player while he was on the floor.

BPM - Box Plus/Minus (available since the 1973-74 season in the NBA); a box score estimate of the points per 100 possessions that a player contributed above a league-average player, translated to an average team.

VORP - Value Over Replacement Player (available since the 1973-74 season in the NBA); a box score estimate of the points per 100 TEAM possessions that a player contributed above a replacement-level (-2.0) player, translated to an average team and prorated to an 82-game season. Multiply by 2.70 to convert to wins over replacement.

DWS- Defensive Win Shares.

OWS - Offensive Win Shares.