FifaSkillsChallenge

August 8, 2020

0.1 Fifa 2018 ML Model for Value Prediction

Andrew Bond Aug 08, 2020

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

We need to load the data and clean it. The data is not encoded with 'utf-8' so we need to load find its encoding and use that instead

[2]:
```
tempdata = open("Skills_Verification_Data_FIFA_18 (2) (1) (1) (1).csv")
print("The file's encoding is ",tempdata.encoding)
fifa_df = pd.read_csv(tempdata,encoding = 'cp1252', low_memory=False).
 ↪dropna(how="all", inplace=False)
fifa_df.head()
```

```
The file's encoding is  cp1252
```

[2]:
```
    No        ID               Name   Age Nationality  Overall  Potential  \
0  0.0  158023.0           L. Messi  31.0   Argentina     94.0       94.0
1  1.0   20801.0  Cristiano Ronaldo  33.0    Portugal     94.0       94.0
2  2.0  190871.0          Neymar Jr  26.0      Brazil     92.0       93.0
3  3.0  193080.0             De Gea  27.0       Spain     91.0       93.0
4  4.0  192985.0       K. De Bruyne  27.0     Belgium     91.0       92.0

                 Club    Value  Wage  … Penalties  Composure  Marking  \
0         FC Barcelona  €110.5M  $565  …      75.0       96.0     33.0
1             Juventus     €77M  $405  …      85.0       95.0     28.0
2  Paris Saint-Germain  €118.5M  $290  …      81.0       94.0     27.0
3    Manchester United     €72M  $260  …      40.0       68.0     15.0
4      Manchester City    €102M  $355  …      79.0       88.0     68.0

  StandingTackle SlidingTackle GKDiving  GKHandling GKKicking GKPositioning  \
0           28.0          26.0      6.0        11.0      15.0          14.0
1           31.0          23.0      7.0        11.0      15.0          14.0
2           24.0          33.0      9.0         9.0      15.0          15.0
```

```
3            21.0           13.0      90.0         85.0       87.0           88.0
4            58.0           51.0      15.0         13.0        5.0           10.0

  GKReflexes
0         8.0
1        11.0
2        11.0
3        94.0
4        13.0

[5 rows x 55 columns]
```

We need to clean some of the data. A lot of columns contain data that can be converted to numerical.

[3]:
```
fifa_df_clean = fifa_df.copy()
fifa_df_clean['Value'] = fifa_df_clean['Value'].replace('[\€M]', '',␣
↪regex=True).astype(float)
fifa_df_clean['Wage'] = fifa_df_clean['Wage'].replace('[\$]', '', regex=True).
↪astype(float)

fifa_df_clean["Height"] = fifa_df_clean["Height"].apply(lambda x: int(x.
↪split("'")[0]) * 12 + int(x.split("'")[1]))

fifa_df_clean["Weight"] = fifa_df_clean["Weight"].
↪replace('[lbs]','',regex=True).astype(float)
```

0.2 Predicting 'Value' with Machine Learning Models

Before even building a model, we can find the features that are most likely to predict 'Value', these variables will have strong positive or negative correlations with 'Value', which indicates that they help explain the variance.

[4]:
```
correlations = fifa_df_clean.corrwith(fifa_df_clean['Value']).
↪sort_values(ascending=False)
print(correlations[abs(correlations) > 0.2])
```

```
Value                       1.000000
Overall                     0.833731
Potential                   0.777904
Wage                        0.754149
Reactions                   0.623651
International Reputation    0.423654
Composure                   0.395891
Finishing                   0.305001
Vision                      0.298988
Agility                     0.297495
Acceleration                0.281586
```

```
Positioning                    0.270860
Volleys                        0.268087
SprintSpeed                    0.258000
BallControl                    0.257387
LongShots                      0.252038
Penalties                      0.250978
ShortPassing                   0.246763
Dribbling                      0.243432
FKAccuracy                     0.241397
Curve                          0.235706
Skill Moves                    0.231791
Balance                        0.225658
LongPassing                    0.210275
Age                           -0.220359
No                            -0.734687
dtype: float64
```

We sorted the correlations in descending order. Clearly 'Value' is perfectly correlated with 'Value', and strangely enough, No is also strongly negatively correlated with the 'Value'. This indicates the rows are in roughly descending order, but is not actually a sensible predictor of 'Value'. We will ignore 'No' and 'Value' and use every other attribute whose correlation is greater than 0.2.

[5]:
```
features = correlations[abs(correlations) > 0.2].index
features = features.drop(['Value','No'])
```

Now we will make a new dataframe with the desired features, and another with the 'Value's. We will then perform our train test split to set aside some rows for validation after training the model.

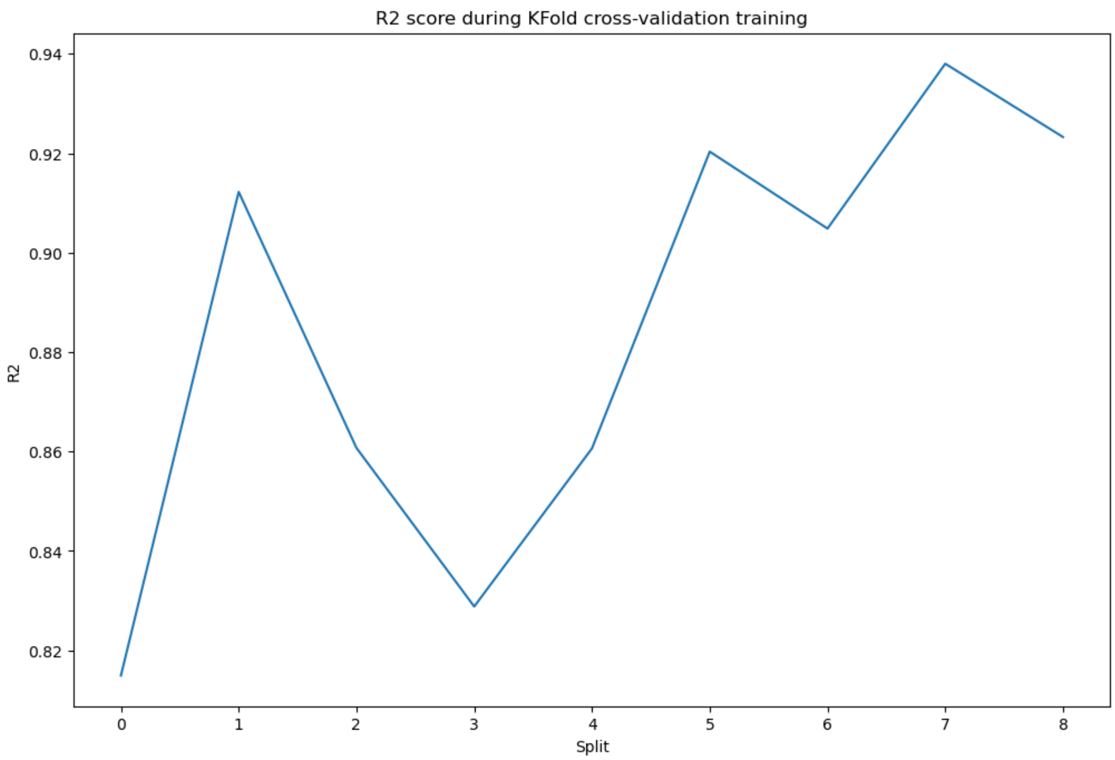
[6]:
```
from sklearn.model_selection import train_test_split
X = fifa_df_clean[features]
y = fifa_df_clean['Value']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
 ↪random_state=5)
```

Ordinary Least Square Regression We will start by training an ordinary least squares regression model on the selected features. Since we are starting with Linear Regression, we are ignoring the variables that could be used categorically. It is possible to make use of them but not necessarily worth the time right off the bat. We could use techniques such as one-hot encoding to try to leverage them in our regression model, but we will not be doing that for now. We will also be using KFold cross-validation method reduce overfitting during training.

[7]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import KFold

fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')

lr_model = LinearRegression()
r2_scores = []
```

```
kfold = KFold(n_splits = 9, shuffle=True, random_state=5)
for i, (train,test) in enumerate(kfold.split(X_train, y_train)):
    lr_model.fit(X_train.iloc[train,:], y_train.iloc[train])
    score = lr_model.score(X_train.iloc[test,:],y_train.iloc[test])
    r2_scores.append(score)

plt.plot(r2_scores)
plt.title('R2 score during KFold cross-validation training')
plt.xlabel('Split')
plt.ylabel('R2')

print("The mean R2 score during the training was ",np.array(r2_scores).mean())
```

```
The mean R2 score during the training was  0.88486356105551
```



Now we can validate the model on the withheld 'test' set.

[8]:
```
validation_score = lr_model.score(X_test,y_test)
print('The R2 on the test set was ', validation_score)
```

```
The R2 on the test set was  0.919977904345087
```

This has a pretty good R2 value, but that just tells us that the regression model does a pretty good job representing the variance in the data set. #### We can determine from the coefficients what the most important variable for prediction is:

[9]:
```
print("The most important feature for predicting 'Value' is ",features[np.
↪argmax(lr_model.coef_)]," which has a coeffient of ",lr_model.coef_.max())
```

```
The most important feature for predicting 'Value' is  Overall  which has a
coeffient of  5.691820876728239
```

There are other ways that we can assess the model performance.

[10]:
```
import sklearn.metrics as metrics
y_train_pred = lr_model.predict(X_train)
y_pred = lr_model.predict(X_test)
print("RMSE:\n Train: ",np.sqrt(metrics.
↪mean_squared_error(y_train,y_train_pred)),"Test: ",np.sqrt(metrics.
↪mean_squared_error(y_test,y_pred)))
print("Max Error:\n Train: ",metrics.max_error(y_train,y_train_pred),"Test:␣
↪",metrics.max_error(y_test,y_pred))
print("Mean Absolute Error:\n Train: ",metrics.
↪mean_absolute_error(y_train,y_train_pred),"Test: ",metrics.
↪mean_absolute_error(y_test,y_pred))
```

```
RMSE:
 Train:  4.982261013093777 Test:  4.259356249221708
Max Error:
 Train:  33.84808006416739 Test:  18.634921567114702
Mean Absolute Error:
 Train:  3.467346061156851 Test:  3.1036554658122224
```

These metrics tell us a little bit more about the performance of our model. The Root Mean Squared error tells us that the standard deviation of our residuals is 4.5 million Euros. The max error shows that the worst prediction we made was off by around 18.5 million(on the test set) and 33.5 million(on the training set) and finally, the Mean Absolute Error tells us that our literal mean error is around 3 million Euros. Scanning the data, these errors seem low in comparison to a lot of the 'Value's, but not all. We can come up with another metric to assess the performance of our model, a heuristic approach. We will find the standard deviation of the 'Value' attribute and use it to give ourselves a threshold or tolerance for the error under which we will declare our model 'Accurate'.

[11]:
```
value_std = fifa_df_clean.Value.std()
print("Standard deviation of the 'Value' variable: ",value_std)
```

```
Standard deviation of the 'Value' variable:  16.51781644769068
```

With this we could calculate our accuracy by determining what number of the predictions are within one standard deviation of their value, but I think we can be a little bit more stringent than that. We will calculate what percentage the standard deviation is of the maximum 'Value' and use that percentage error as our tolerance for accuracy.

```
[12]: max_value = fifa_df_clean.Value.max()
tolerance = value_std/max_value
print("Our tolerance will be ", tolerance*100, "%")
```

```
Our tolerance will be  13.939085609865554 %
```

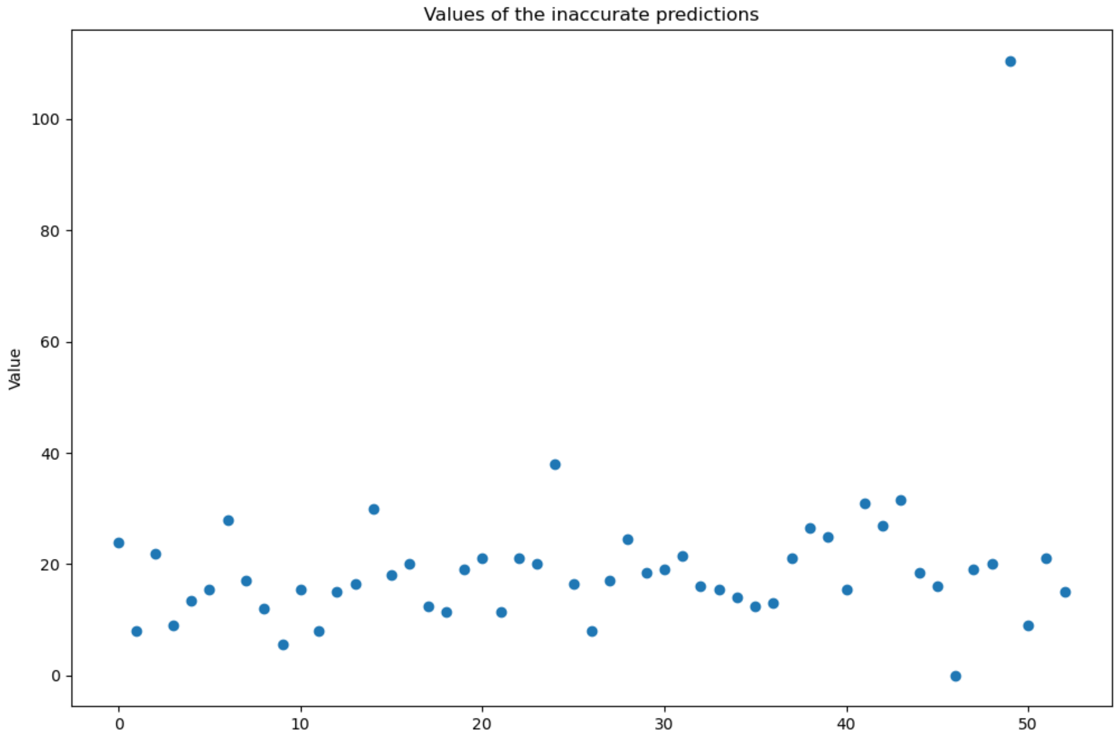
```
[13]: residuals = (y_pred - y_test)
no_accurate = residuals[abs(residuals)/y_test <= tolerance].count()
print("With this new threshold tolerance for accuracy, we have an accuracy of:␣
 ↪",no_accurate/y_test.count()*100 , "%")
```

```
With this new threshold tolerance for accuracy, we have an accuracy of:
64.90066225165563 %
```

Not bad! With our Ordinary Least Squares regression model and our somewhat stringent metric, we managed to achieve an accuracy of ~65% using less than 25 variables. Our metric required that our prediction was within ~13.9% of the true value. Let's take a look at the values for which we weren't able to make this threshold.

```
[14]: wrong = residuals[abs(residuals)/y_test > tolerance]
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
plt.scatter(range(wrong.count()),y_test[wrong.index])
plt.title('Values of the inaccurate predictions')
plt.xlabel('')
plt.ylabel('Value')
print("The mean value of the wrong predictions is: ",y_test[wrong.index].mean())
print("The threshold for the mean of the incorrect predictions is:␣
 ↪",y_test[wrong.index].mean()*tolerance)
```

```
The mean value of the wrong predictions is:  19.5188679245283
The threshold for the mean of the incorrect predictions is:  2.7207517100765877
```



We should expect that the threshold would be harder to meet for the lower 'Value's. The mean of the missed values is 19.5 million, the threshold 13.9% for this mean is around 2.7 million. For a dataset that includes 'Value's over 100 million, this is pretty precise and its no surprise that the model couldn't manage accuracy on these players. This could potentially be addressed by categorical variables or by removing outliers. We will examine outliers such as "Superstars" later as a business question.

Decision Trees and more We also want to try to take advantage of our categorical variables, which will require a little bit more cleaning to prepare. These variables can be very valuable to decision trees and algorithms like Ada Boost and Random Forests. We will use these and see how well they perform.

We start with the cleaning, I have identified some columns as great categorical candidates to inform our model:

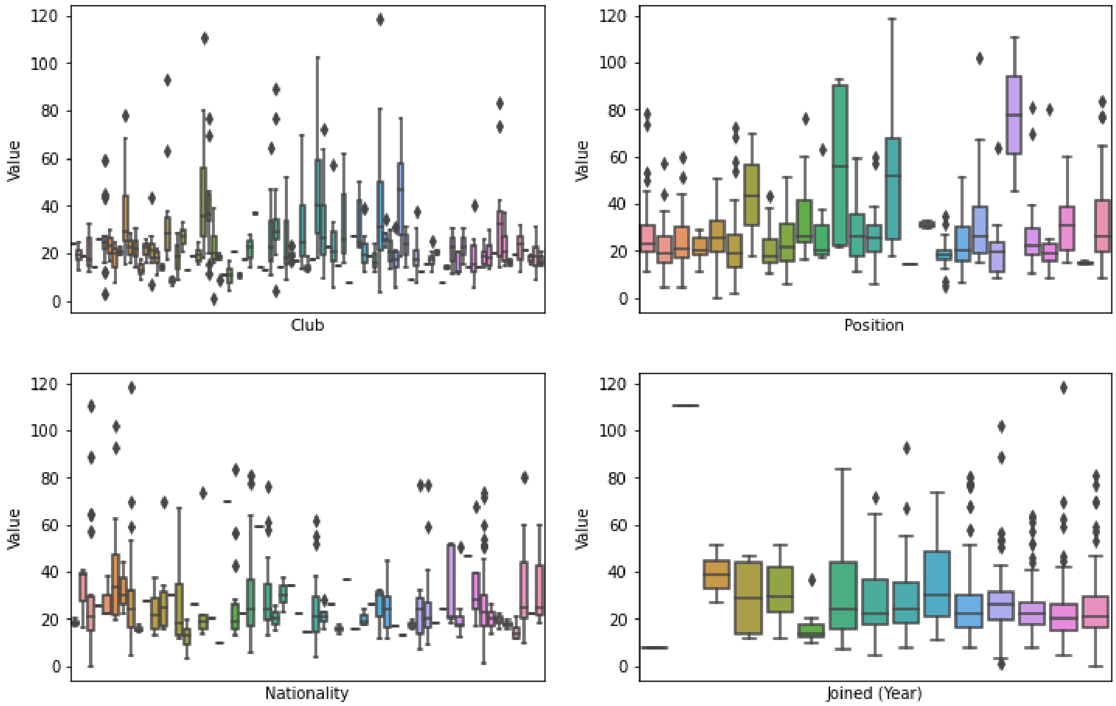
[15]:
```
fifa_df_clean["Nationality"] = fifa_df_clean["Nationality"].astype("category")
fifa_df_clean["Club"] = fifa_df_clean["Club"].astype("category")
fifa_df_clean["Preferred Foot"] = fifa_df_clean['Preferred Foot'].
 ↪astype("category")

fifa_df_clean["Work Rate"] = fifa_df_clean["Work Rate"].astype("category")
fifa_df_clean["Position"] = fifa_df_clean["Position"].astype("category")
```

```
fifa_df_clean.insert(fifa_df_clean.columns.get_loc("Joined") + 1, "Joined␣
↪(Month)", pd.DatetimeIndex(pd.to_datetime(fifa_df_clean["Joined"])).
↪strftime("%b").astype('category'))
fifa_df_clean["Joined (Month)"] = fifa_df_clean["Joined (Month)"].cat.
↪reorder_categories(['Jan', 'Feb', 'Mar', 'Apr', 'May','Jun','Jul',␣
↪'Aug','Sep','Oct','Nov', 'Dec'])
fifa_df_clean["Joined (Month)"] = fifa_df_clean["Joined (Month)"].fillna('Jul')

fifa_df_clean.insert(fifa_df_clean.columns.get_loc("Joined") + 2, "Joined␣
↪(Year)", pd.DatetimeIndex(pd.to_datetime(fifa_df_clean["Joined"])).year)
fifa_df_clean["Joined (Year)"] = fifa_df_clean["Joined (Year)"].fillna(2018)
```

We can take a look at a few of these variables and see if they have clear "classes" amongst them.

[16]:
```
fig, ax = plt.subplots(2,2, figsize=(12,8))

for j in range(len(ax)):
    for i in range(len(ax[j])):
        ax[j][i].set_xlabel('label')

ax[0][0] = sns.boxplot(x="Club", y="Value", data=fifa_df_clean, ax=ax[0][0])
ax[1][0] = sns.boxplot(x="Nationality", y="Value", data=fifa_df_clean,␣
↪ax=ax[1][0])
ax[0][1] = sns.boxplot(x="Position", y="Value", data=fifa_df_clean, ax=ax[0][1])
ax[1][1] = sns.boxplot(x="Joined (Year)", y="Value", data=fifa_df_clean,␣
↪ax=ax[1][1])

for j in range(len(ax)):
    for i in range(len(ax[j])):
        ax[j][i].set_xticks([])

fig.show()
```

```
C:\Users\andyr\anaconda3\lib\site-packages\ipykernel_launcher.py:16:
UserWarning: Matplotlib is currently using
module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot
show the figure.
  app.launch_new_instance()
```



It does appear that we have some separate classes going on here. We can also see many of the outliers that probably caused us issues with the Linear Regression model. We will use the codes for the categories rather than the category names themselves.

[17]:
```
fifa_df_clean["Nationality"] = fifa_df_clean["Nationality"].cat.codes
fifa_df_clean["Preferred Foot"] = fifa_df_clean["Preferred Foot"].cat.codes
fifa_df_clean["Work Rate"] = fifa_df_clean["Work Rate"].cat.codes
fifa_df_clean["Position"] = fifa_df_clean["Position"].cat.codes
fifa_df_clean["Joined (Month)"] = fifa_df_clean["Joined (Month)"].cat.codes
fifa_df_clean["Club"] = fifa_df_clean["Club"].cat.codes
```

We are also going to include the variables that have the good correlation with 'Value'.

[18]:
```
features = features.append(pd.Index(['Nationality','Preferred Foot','Work␣
↪Rate','Position','Joined (Month)','Club']))
X_dt = fifa_df_clean[features]
y_dt = fifa_df_clean['Value']
X_dt_train, X_dt_test, y_dt_train, y_dt_test = train_test_split(X_dt, y_dt,␣
↪test_size = 0.3, random_state=5)
```

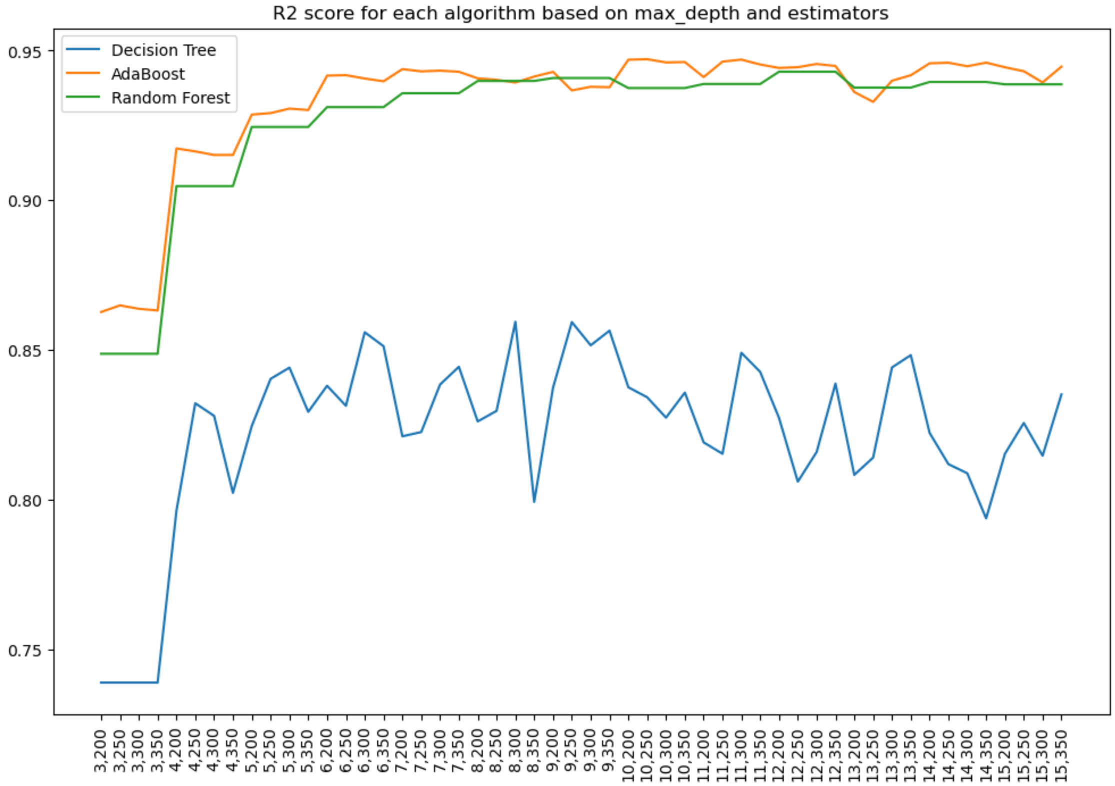
We are going to use Decision Trees, the most basic. Ada Boost to provide a refined Decision Tree with more and more accurate classes and a Random Forest.

[19]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import AdaBoostRegressor, RandomForestRegressor
```

[20]:
```
def train_trees(max_depth, n_estimators, random_state):
    dtmodel = DecisionTreeRegressor(max_depth = max_depth)
    abmodel = AdaBoostRegressor(DecisionTreeRegressor(max_depth = max_depth),␣
 ↪n_estimators = n_estimators, random_state = random_state)
    rfmodel = RandomForestRegressor(max_depth=max_depth, random_state =␣
 ↪random_state)

    dtmodel.fit(X_dt_train, y_dt_train)
    abmodel.fit(X_dt_train, y_dt_train)
    rfmodel.fit(X_dt_train, y_dt_train)

    dtscore = dtmodel.score(X_dt_test,y_dt_test)
    abscore = abmodel.score(X_dt_test,y_dt_test)
    rfscore = rfmodel.score(X_dt_test,y_dt_test)

    return (dtmodel,abmodel,rfmodel,dtscore,abscore,rfscore)
```

[21]:
```
dtscores = []
abscores = []
rfscores = []
labels = []
for i in range(3,16):
    for j in np.arange(200, 351, 50):
        (_,_,_,dts,abs,rfs) = train_trees(i, j, 5)
        labels.append(str(i)+','+str(j))
        dtscores.append(dts)
        abscores.append(abs)
        rfscores.append(rfs)
```

[22]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
plt.plot(labels,dtscores)
plt.plot(labels,abscores)
plt.plot(labels,rfscores)
plt.title("R2 score for each algorithm based on max_depth and estimators")
plt.legend(["Decision Tree","AdaBoost","Random Forest"])
locs, lab = plt.xticks()
plt.setp(lab, rotation=90);
```



AdaBoost and the Random Forest level out for the most part sowe will choose one of the options for AdaBoost that spikes around a max_depth of 13, say 13,250

[23]:
```
(_,ab,_,_,_,_) = train_trees(13,250,5)
y_ab_train_pred = ab.predict(X_dt_train)
y_ab_pred = ab.predict(X_dt_test)
print("RMSE:\n Train: ",np.sqrt(metrics.
 ↪mean_squared_error(y_dt_train,y_ab_train_pred)),"Test: ",np.sqrt(metrics.
 ↪mean_squared_error(y_dt_test,y_ab_pred)))
print("Max Error:\n Train: ",metrics.
 ↪max_error(y_dt_train,y_ab_train_pred),"Test: ",metrics.
 ↪max_error(y_dt_test,y_ab_pred))
print("Mean Absolute Error:\n Train: ",metrics.
 ↪mean_absolute_error(y_dt_train,y_ab_train_pred),"Test: ",metrics.
 ↪mean_absolute_error(y_dt_test,y_ab_pred))
```

```
RMSE:
 Train:  0.43728182580772934 Test:  3.9020154513592082
Max Error:
 Train:  2.5 Test:  20.0
Mean Absolute Error:
 Train:  0.16486263736263737 Test:  2.225953105423304
```

The results above make are suspicious of some overfitting, but the metrics are still pretty good, we will move on to calculating our heuristic.

[24]:
```
residuals_ab = (y_ab_pred - y_dt_test)
no_accurate_ab = residuals_ab[np.abs(residuals_ab)/y_dt_test <= tolerance].
 ↪count()
print("With this new threshold tolerance for accuracy, we have an accuracy of:␣
 ↪",no_accurate_ab/y_dt_test.count()*100 , "%")
```

```
With this new threshold tolerance for accuracy, we have an accuracy of:
82.11920529801324 %
```

With this method we got an accuracy of 82%, which is quite good! To improve this score we could also spent some time playing around with features, and investigating the possibility of overfitting as possibly indicated from the features above. We will determine the most important feature really quickly.

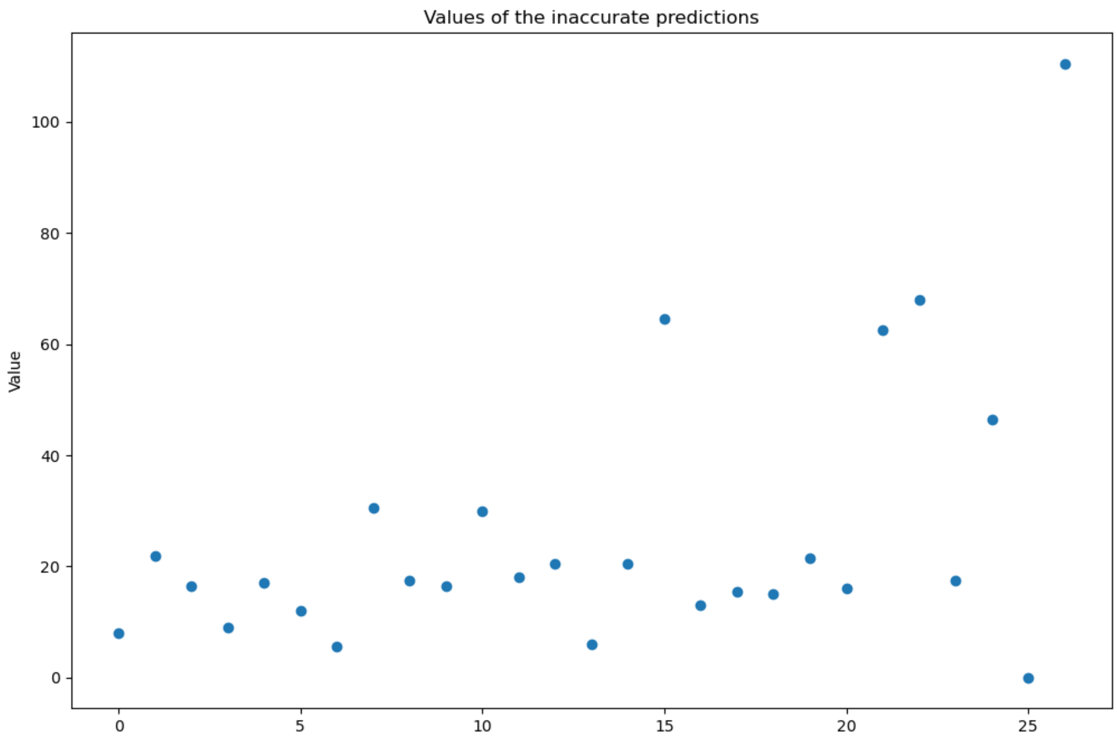
[25]:
```
top_features = np.array(ab.feature_importances_).argsort()[::-1][:5]
print("The top 5 features are:")
for i in range(len(top_features)):
    print(features[top_features[i]])
```

```
The top 5 features are:
Potential
Overall
Reactions
Wage
Age
```

Like before we will look at the Values of the rows that we mis-predicted.

[26]:
```
wrong_ab = residuals_ab[np.abs(residuals_ab)/y_dt_test > tolerance]
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
plt.scatter(range(wrong_ab.count()),y_dt_test[wrong_ab.index])
plt.title('Values of the inaccurate predictions')
plt.xlabel('')
plt.ylabel('Value')
print("The mean value of the wrong predictions is: ",y_dt_test[wrong_ab.index].
 ↪mean())
print("The threshold for the mean of the incorrect predictions is:␣
 ↪",y_dt_test[wrong_ab.index].mean()*tolerance)
```

```
The mean value of the wrong predictions is:  25.925925925925927
The threshold for the mean of the incorrect predictions is:  3.6138370099651436
```



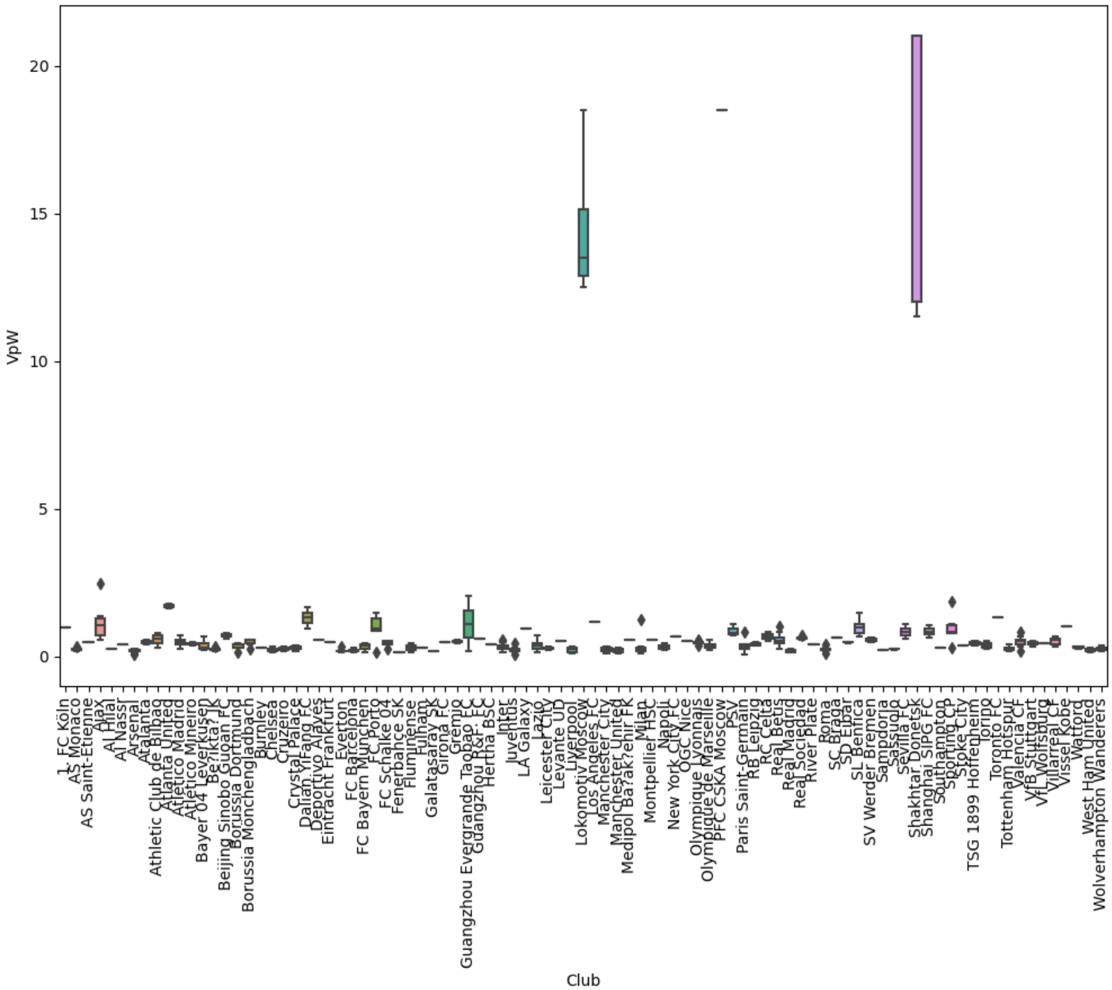
While we have much fewer inaccurate predictions, the average is a bit higher and we see some errors right in the middle range. With more time we could take a look at why this is happening. It also seems that accounting for outliers may help quite a bit with the training of these models as well. We could also take a look at other models for the regression problem, or penalties such as Ridge, Lasso or Elastic Net. We could also examine the bias versus the variance in our models to try to find the right balance. But for now, this is all we are going to do when it comes to the prediction of Value.

0.3 Data Exploration and Business Questions

While cleaning the data for the machine learning models, I became interested in the effects of the classes such as 'Club'. I think that a good starting place for exploration and an appropriate Business question is, "How do 'Value's distribute amongst these Clubs". With that in mind we will start splitting up the data and visualizing it. To examine this question, we will create a new attribute, $VpW = \frac{Value}{Wage}$ which can help us identify business value of a player. We also need to bring our categories back to make sense of what we see.

[27]:
```
fifa_df_clean['VpW'] = fifa_df_clean['Value']/fifa_df_clean['Wage']
fifa_df_clean["Nationality"] = fifa_df["Nationality"].astype("category")
fifa_df_clean["Club"] = fifa_df["Club"].astype("category")
fifa_df_clean["Preferred Foot"] = fifa_df['Preferred Foot'].astype("category")

fifa_df_clean["Work Rate"] = fifa_df["Work Rate"].astype("category")
fifa_df_clean["Position"] = fifa_df["Position"].astype("category")
```

[28]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
sns.boxplot(x="Club", y="VpW", data=fifa_df_clean)
locs, lab = plt.xticks()
plt.setp(lab, rotation=90);
```



Clearly something fishy is going on here, we can look at the data to find out why these Clubs have such a atypical distribution of VpW's

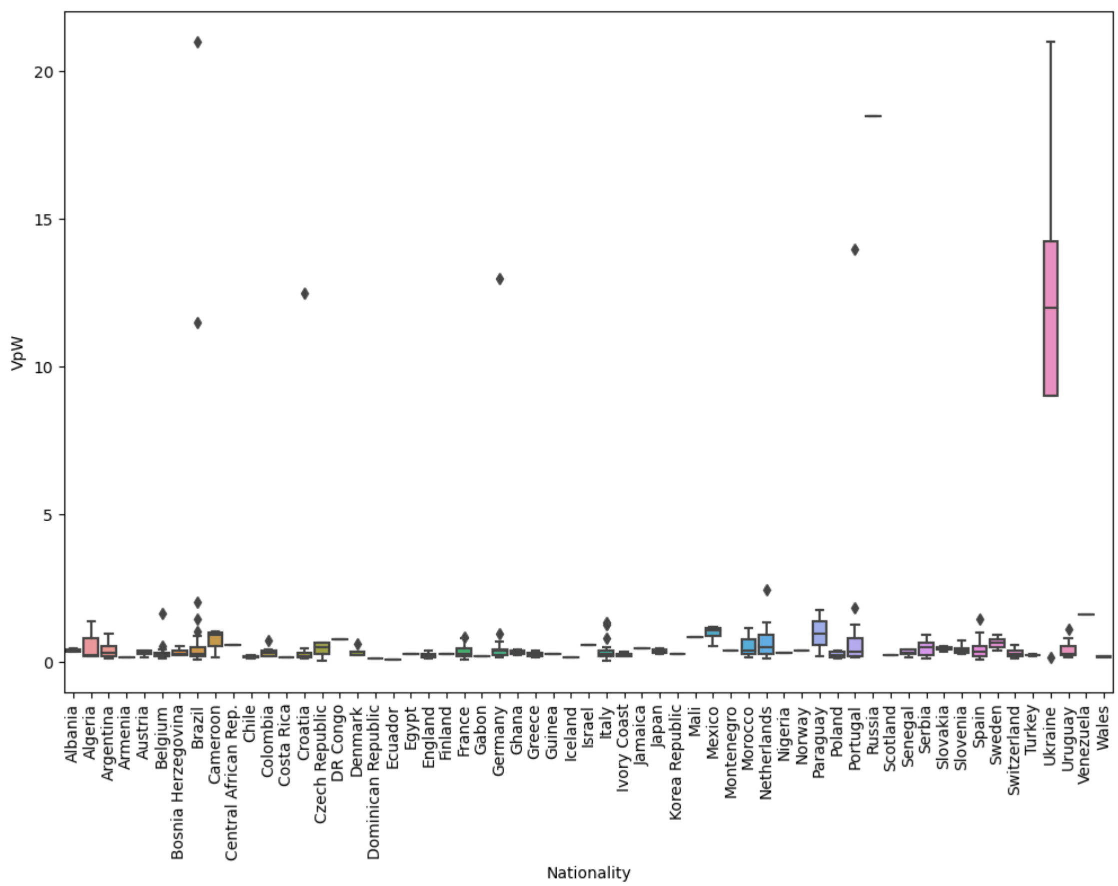
[29]:
```
clubs = (fifa_df_clean['Club'] == "Shakhtar Donetsk") |  (fifa_df_clean['Club']␣
↪== "Lokomotiv Moscow")
df_vpw_outliers = fifa_df_clean[clubs]
df_vpw_outliers.Wage
```

[29]:
```
286    1.0
288    1.0
301    1.0
```

```
381    1.0
386    1.0
405    1.0
453    1.0
473    1.0
484    1.0
Name: Wage, dtype: float64
```

Well, it appears that some of these clubs are not paying their players or don't release Wage information, it could also be clerical errors or perhaps autofilled due to lack of data. In reality, this would be a time to go talk to a subject matter expert and figure out what is going on with our data, but we will forge ahead with the assumption that we can hire the players for the wages given. Let's take a look if this lack of pay is related to Nationality.

[30]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
sns.boxplot(x="Nationality", y="VpW", data=fifa_df_clean)
locs, lab = plt.xticks()
plt.setp(lab, rotation=90);
```



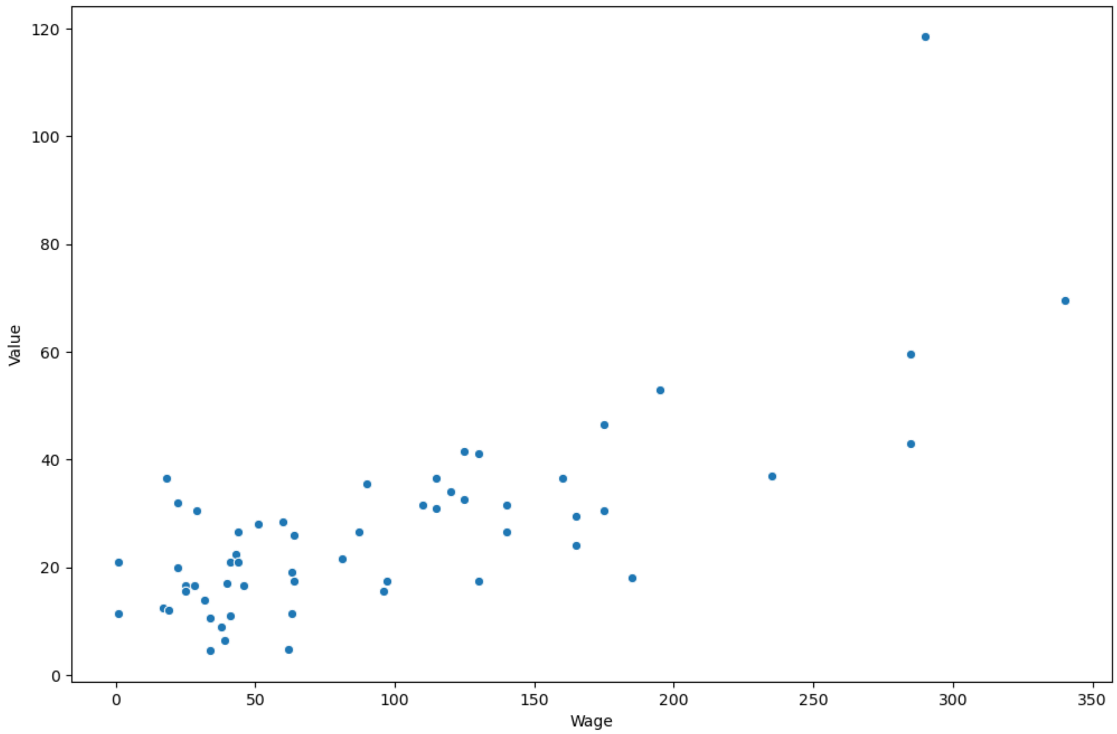
[31]:
```
countries = (fifa_df_clean['Nationality'] == "Ukraine") | ␣
↪(fifa_df_clean['Nationality'] == "Russia")
df_vpw_outliers = fifa_df_clean[clubs]
df_vpw_outliers.Wage
```

[31]:
```
286    1.0
288    1.0
301    1.0
381    1.0
386    1.0
405    1.0
453    1.0
473    1.0
484    1.0
Name: Wage, dtype: float64
```

We found the same indices by looking at wages for Ukraine and Russia, so it seems like these anomolies in the data are related to the country that the player is from. I don't think we can do any more with these underpaid players without more background information so instead we will try to figure out what is going on with the other outliers.

[32]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
outliers = fifa_df_clean['Nationality'] == "Brazil"
df_vpw_outliers = fifa_df_clean[outliers]
sns.scatterplot(x ='Wage', y='Value', data = df_vpw_outliers)
```

[32]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x17effa342c8>
```



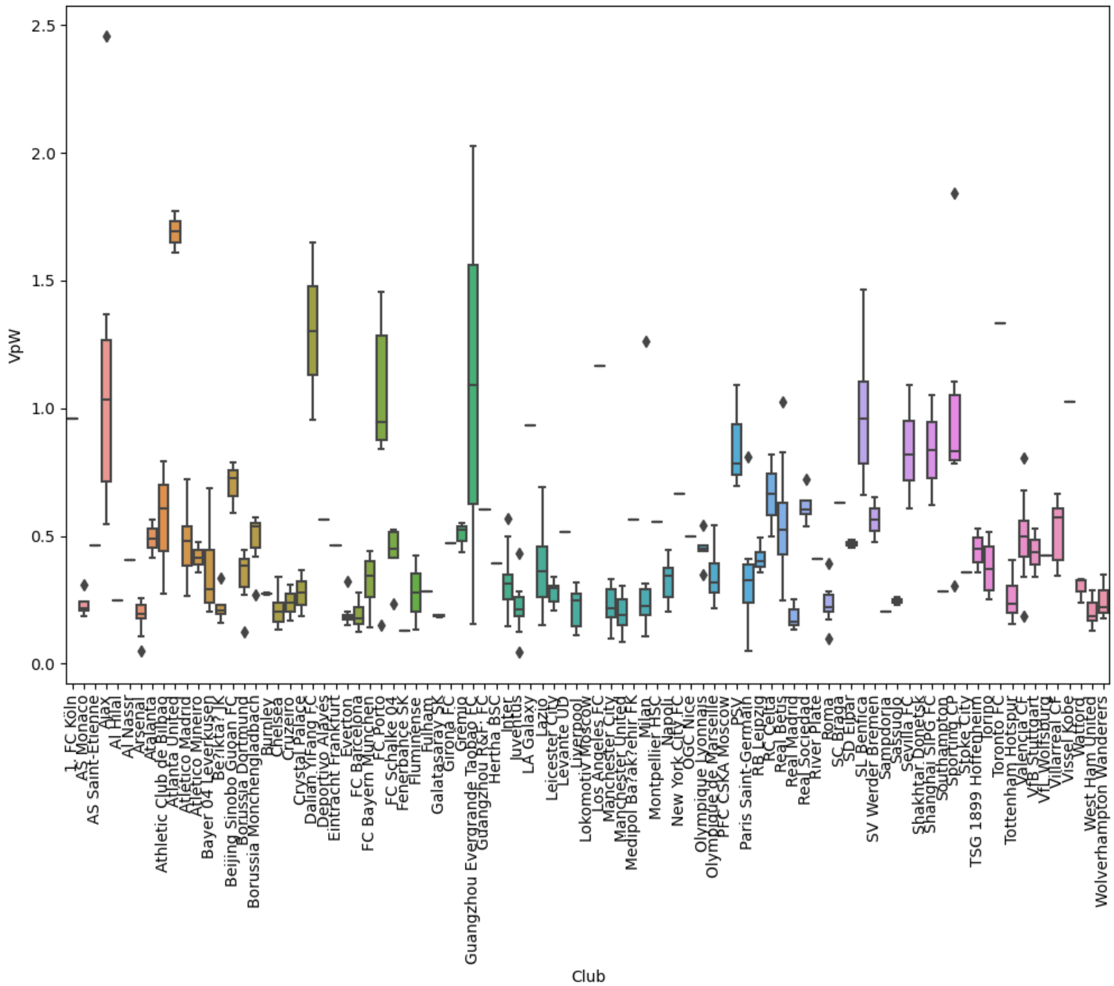
Once again, it seems like we have some underpaid players. My guess is that unless we eliminate these ridiculously low wages, we would use this data to put together a team of players whose cost is not representative of reality. We could use a Linear Regression model or other Machine Learning model trained on the players whose Wage is greater than 1, and reassign Wage for the players. For the sake of time we will just remove the players whose Wage is 1.

[33]:
```
fifa_df_wage = fifa_df_clean[fifa_df_clean['Wage'] > 1]
print(len(fifa_df_wage))
```

```
490
```

Now that we got rid of those irrationally paid players, we will look at Clubs again.

[34]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
sns.boxplot(x="Club", y="VpW", data=fifa_df_wage)
locs, lab = plt.xticks()
plt.setp(lab, rotation=90);
```



Things look a lot more interesting now, and it is clear that the Clubs have very different distributions of VpW. Since there are 23 players on a FIFA team (I looked it up) let's take a look at the top 23 'VpW' players and their wages.

[35]:
```
top_vpw = fifa_df_wage.sort_values(by=['VpW'], ascending=False).iloc[:23]
top_vpw[['Name','Wage','VpW','Value']]
```

[35]:

	Name	Wage	VpW	Value
226	M. de Ligt	11.0	2.454545	27.0
166	Anderson Talisca	18.0	2.027778	36.5
114	Bruno Fernandes	22.0	1.840909	40.5
418	M. Almirón	11.0	1.772727	19.5
173	Y. Carrasco	20.0	1.650000	33.0
345	J. Martínez	14.0	1.607143	22.5
342	Grimaldo	14.0	1.464286	20.5
112	Alex Telles	22.0	1.454545	32.0
94	Y. Brahimi	28.0	1.392857	39.0

```
323        F. de Jong  19.0  1.368421   26.0
293       S. Giovinco  15.0  1.333333   20.0
187    Danilo Pereira  21.0  1.285714   27.0
229     G. Donnarumma  23.0  1.260870   29.0
371         J. Corona  18.0  1.194444   21.5
397           C. Vela  15.0  1.166667   17.5
171         H. Ziyech  28.0  1.160714   32.5
194             Pizzi  22.0  1.159091   25.5
274         S. Coates  19.0  1.105263   21.0
329         H. Lozano  22.0  1.090909   24.0
170         Q. Promes  28.0  1.089286   30.5
436              Rafa  17.0  1.088235   18.5
205             Oscar  29.0  1.051724   30.5
426          A. Onana  14.0  1.035714   14.5
```

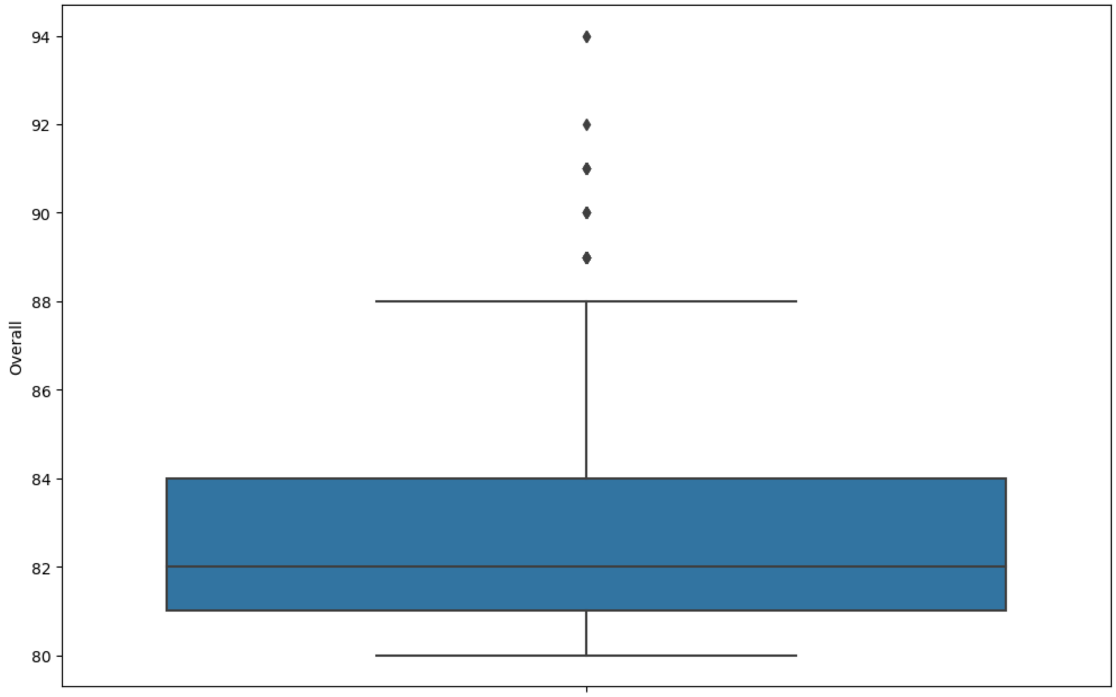
[36]:
```
print("Using our top 23 VpW players, we get a team that costs us: ")
print("$",top_vpw['Wage'].sum())
print("This budget team gives us a Value of: ")
print(top_vpw['Value'].sum()," million Euros")
```

```
Using our top 23 VpW players, we get a team that costs us:
$ 450.0
This budget team gives us a Value of:
608.5  million Euros
```

For less than a single one of the "superstars", we can get a value of 608.5 million Euros, probably 6 times the value of a superstar…but that is our entire team. Great on a budget, but could we actually win any games? We can't answer that question with our data, but we can certainly look at our "Overall" scores and whether we even have the right players for the positions we need! Before we look at our team, lets get an idea of what the "Overall" scores look like amongst our data. We also should take a look what what positions we need to put together a legitimate team.

[37]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
sns.boxplot(y="Overall", data=fifa_df_clean)
locs, lab = plt.xticks()
plt.setp(lab, rotation=90);
print("The mean 'Overall' score of a player in our data is: ",fifa_df_clean.
 ↪Overall.mean())
```

```
The mean 'Overall' score of a player in our data is:  82.8942115768463
```



So, the average for players in our data is right around 82. Next, we look into team compositions and viable team strategies. I used the following site Soccer Team Composition. With what we know, lets take a look at our “Budget” team.

[38]:
```
print("Our team's mean 'Overall' score is: ", top_vpw.Overall.mean())
top_vpw[['Name','Position','Overall']]
```

```
Our team's mean 'Overall' score is:  82.08695652173913
```

[38]:

	Name	Position	Overall
226	M. de Ligt	RCB	82.0
166	Anderson Talisca	CAM	83.0
114	Bruno Fernandes	LCM	84.0
418	M. Almirón	CAM	80.0
173	Y. Carrasco	LM	83.0
345	J. Martínez	LS	81.0
342	Grimaldo	LB	81.0
112	Alex Telles	LB	84.0
94	Y. Brahimi	LM	85.0
323	F. de Jong	LDM	81.0
293	S. Giovinco	CF	82.0
187	Danilo Pereira	CDM	83.0
229	G. Donnarumma	GK	82.0
371	J. Corona	RM	81.0
397	C. Vela	RW	81.0

```
171        H. Ziyech      RAM     83.0
194            Pizzi      LCM     83.0
274        S. Coates      RCB     82.0
329        H. Lozano       LS     81.0
170        Q. Promes       RM     83.0
436             Rafa       RW     80.0
205            Oscar      LCM     83.0
426         A. Onana       GK     80.0
```

Already, we know that our team is slightly below average. As for player positions, we have a bunch of Acronyms, lets use the categories from the link above to analyze if we can manage to put together a '4-3-3' or '4-4-2' formation. For Defensive Positions we have ['CB','LB','RB','LWB','RWB','SW'] For Midfield Positions we have ['DM','CM','AM','LM','RM'] For Offensive Positions we have ['CF','S','SS'] And we always need a ['GK'] Let's make a new column to label our players.

[39]:
```
defensive = ['CB','LB','RB','LWB','RWB','SW']
midfield = ['DM','CM','AM','LM','RM']
offensive = ['CF','S','SS']
offMid = ['RW','LW','LF','RF']
# I added wings(RW, LW, LF, RF) after looking at https://www.fifauteam.com/
 ↪fifa-ultimate-team-positions-and-tactics/
goalkeeper = ['GK']
top_vpw['Position Type'] = top_vpw['Position'].apply(lambda x: "Defense" if␣
 ↪any(pos in x for pos in defensive)
                                                    else "Midfield"␣
 ↪if any(pos in x for pos in midfield)
                                                    else␣
 ↪"Offensive" if any(pos in x for pos in offensive)
                                                    else "OffMid"␣
 ↪if any(pos in x for pos in offMid)
                                                    else "Goalie"␣
 ↪if "GK" in x
                                                    else "Error")
```

[40]:
```
top_vpw[['Position','Position Type']]
```

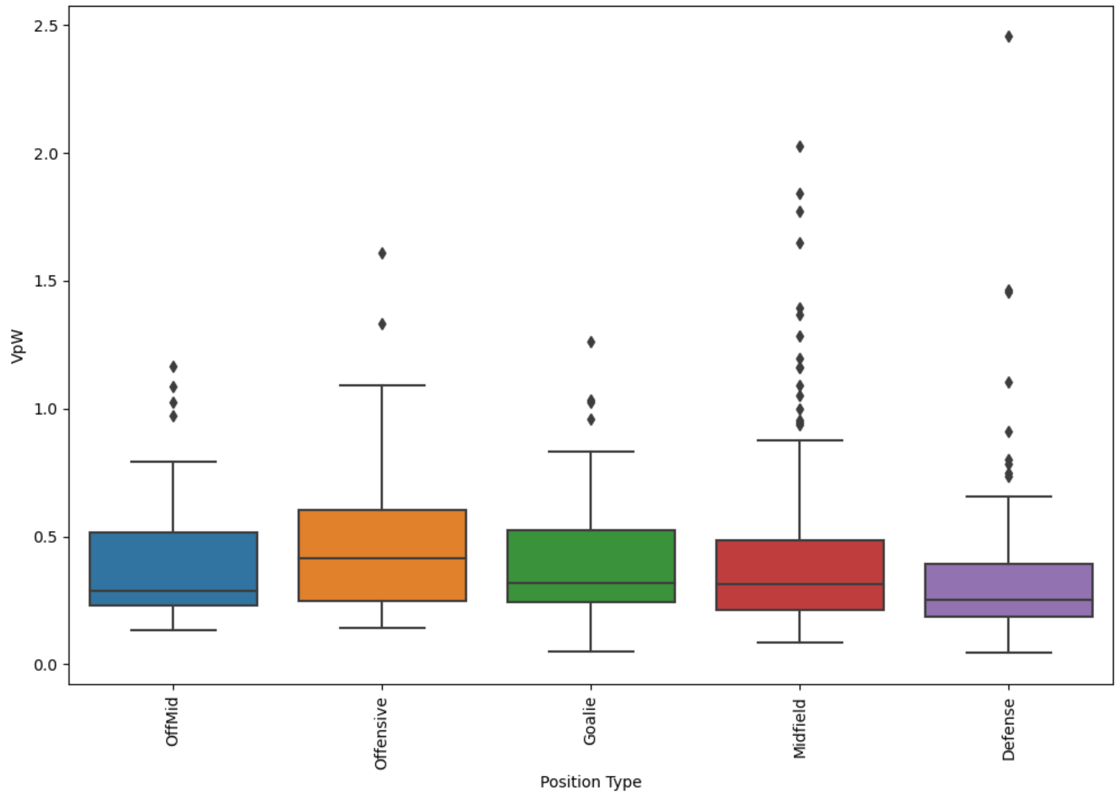
[40]:
```
    Position Position Type
226      RCB       Defense
166      CAM      Midfield
114      LCM      Midfield
418      CAM      Midfield
173       LM      Midfield
345       LS     Offensive
342       LB       Defense
112       LB       Defense
94        LM      Midfield
323      LDM      Midfield
```

```
293        CF    Offensive
187       CDM     Midfield
229        GK       Goalie
371        RM     Midfield
397        RW       OffMid
171       RAM     Midfield
194       LCM     Midfield
274       RCB      Defense
329        LS    Offensive
170        RM     Midfield
436        RW       OffMid
205       LCM     Midfield
426        GK       Goalie
```

It looks like we can put together a team, but we would have no backup Defense players if we played a 4-x-x. We have a massive number of Midfielders, two Goalies and five Offensive players. I think we could probably put together a lot better team composition and probably achieve a better 'Overall' score as well. For our next business question, we are going to take a closer look at positions and put together a team based on a proposed composition.

[41]:
```
fifa_df_clean['Position Type'] = fifa_df_clean['Position'].apply(lambda x:␣
↪"Defense" if any(pos in x for pos in defensive)
                                                                else "Midfield"␣
↪if any(pos in x for pos in midfield)
                                                                else␣
↪"Offensive" if any(pos in x for pos in offensive)
                                                                else "OffMid"␣
↪if any(pos in x for pos in offMid)
                                                                else "Goalie"␣
↪if "GK" in x
                                                                else "Error")
fifa_df_positions = fifa_df_clean[fifa_df_clean.Wage > 1]
```

[42]:
```
fig=plt.figure(figsize=(12,8), dpi= 100, facecolor='w', edgecolor='k')
sns.boxplot(x="Position Type", y="VpW", data=fifa_df_positions)
locs, lab = plt.xticks()
plt.setp(lab, rotation=90);
```



Let's put together a team! We want to grab the top 5 dedicated Offense, the top 4 dedicated Midfield, the top 4 Offensive/Midfield, the top 7 Defensive, and the top 3 Goalies.

[43]:
```
offMid_df = fifa_df_positions[fifa_df_positions["Position Type"] == "OffMid"]
offensive_df = fifa_df_positions[fifa_df_positions["Position Type"] ==␣
 ↪"Offensive"]
midfield_df = fifa_df_positions[fifa_df_positions["Position Type"] ==␣
 ↪"Midfield"]
defensive_df = fifa_df_positions[fifa_df_positions["Position Type"] ==␣
 ↪"Defense"]
goalie_df = fifa_df_positions[fifa_df_positions["Position Type"] == "Goalie"]
top_OffMid = offMid_df.sort_values(by=['VpW'], ascending=False).iloc[:4]
top_offensive = offensive_df.sort_values(by=['VpW'], ascending=False).iloc[:5]
top_defensive = defensive_df.sort_values(by=['VpW'], ascending=False).iloc[:7]
top_midfield = midfield_df.sort_values(by=['VpW'], ascending=False).iloc[:4]
top_goalie = goalie_df.sort_values(by=['VpW'], ascending=False).iloc[:3]
our_team = top_OffMid.append([top_offensive,␣
 ↪top_defensive,top_midfield,top_goalie])
our_team
```

[43]:

	No	ID	Name	Age	Nationality	Overall	Potential	\
397	397.0	169416.0	C. Vela	29.0	Mexico	81.0	81.0	
436	436.0	216547.0	Rafa	25.0	Portugal	80.0	83.0	
76	76.0	41.0	Iniesta	34.0	Spain	86.0	86.0	
375	375.0	190972.0	E. Salvio	27.0	Argentina	81.0	81.0	
345	345.0	207877.0	J. Martínez	25.0	Venezuela	81.0	84.0	
293	293.0	184431.0	S. Giovinco	31.0	Italy	82.0	82.0	
329	329.0	221992.0	H. Lozano	22.0	Mexico	81.0	86.0	
204	204.0	189068.0	B. Dost	29.0	Netherlands	83.0	83.0	
480	480.0	199069.0	V. Aboubakar	26.0	Cameroon	80.0	82.0	
226	226.0	235243.0	M. de Ligt	18.0	Netherlands	82.0	91.0	
342	342.0	210035.0	Grimaldo	22.0	Spain	81.0	87.0	
112	112.0	212462.0	Alex Telles	25.0	Brazil	84.0	87.0	
274	274.0	197655.0	S. Coates	27.0	Uruguay	82.0	83.0	
175	175.0	207863.0	Felipe	29.0	Brazil	83.0	83.0	
488	488.0	194022.0	André Almeida	27.0	Portugal	80.0	80.0	
428	428.0	224334.0	M. Acuña	26.0	Argentina	80.0	80.0	
166	166.0	212523.0	Anderson Talisca	24.0	Brazil	83.0	90.0	
114	114.0	212198.0	Bruno Fernandes	23.0	Portugal	84.0	88.0	
418	418.0	230977.0	M. Almirón	24.0	Paraguay	80.0	84.0	
173	173.0	208418.0	Y. Carrasco	24.0	Belgium	83.0	86.0	
229	229.0	230621.0	G. Donnarumma	19.0	Italy	82.0	93.0	
426	426.0	226753.0	A. Onana	22.0	Cameroon	80.0	85.0	
237	237.0	221087.0	Pau López	23.0	Spain	82.0	87.0	

	Club	Value	Wage	…	Marking	StandingTackle	\
397	Los Angeles FC	17.5	15.0	…	31.0	22.0	
436	SL Benfica	18.5	17.0	…	23.0	38.0	
76	Vissel Kobe	21.5	21.0	…	67.0	57.0	
375	SL Benfica	18.5	19.0	…	49.0	60.0	
345	Atlanta United	22.5	14.0	…	20.0	20.0	
293	Toronto FC	20.0	15.0	…	23.0	29.0	
329	PSV	24.0	22.0	…	45.0	35.0	
204	Sporting CP	26.0	26.0	…	38.0	45.0	
480	FC Porto	18.0	19.0	…	44.0	23.0	
226	Ajax	27.0	11.0	…	84.0	84.0	
342	SL Benfica	20.5	14.0	…	73.0	78.0	
112	FC Porto	32.0	22.0	…	80.0	81.0	
274	Sporting CP	21.0	19.0	…	84.0	85.0	
175	FC Porto	20.0	22.0	…	85.0	85.0	
488	SL Benfica	12.0	15.0	…	82.0	82.0	
428	Sporting CP	12.5	16.0	…	78.0	80.0	
166	Guangzhou Evergrande Taobao FC	36.5	18.0	…	55.0	62.0	
114	Sporting CP	40.5	22.0	…	63.0	66.0	
418	Atlanta United	19.5	11.0	…	43.0	53.0	
173	Dalian YiFang FC	33.0	20.0	…	58.0	39.0	
229	Milan	29.0	23.0	…	20.0	14.0	

426	Ajax	14.5	14.0	…	12.0	18.0
237	Real Betis	21.5	21.0	…	19.0	20.0

	SlidingTackle	GKDiving	GKHandling	GKKicking	GKPositioning	GKReflexes	\
397	14.0	8.0	14.0	8.0	13.0	10.0	
436	31.0	9.0	11.0	11.0	12.0	8.0	
76	56.0	6.0	13.0	6.0	13.0	7.0	
375	56.0	9.0	11.0	9.0	5.0	14.0	
345	15.0	12.0	14.0	14.0	12.0	8.0	
293	28.0	6.0	3.0	6.0	3.0	3.0	
329	29.0	11.0	10.0	14.0	14.0	10.0	
204	26.0	6.0	12.0	15.0	11.0	8.0	
480	19.0	8.0	10.0	9.0	7.0	8.0	
226	79.0	12.0	11.0	11.0	12.0	10.0	
342	79.0	7.0	13.0	10.0	7.0	13.0	
112	79.0	13.0	8.0	12.0	11.0	14.0	
274	85.0	16.0	13.0	15.0	16.0	13.0	
175	79.0	9.0	11.0	14.0	9.0	7.0	
488	79.0	14.0	6.0	7.0	12.0	8.0	
428	75.0	8.0	14.0	13.0	13.0	14.0	
166	42.0	13.0	11.0	13.0	12.0	10.0	
114	53.0	12.0	14.0	15.0	8.0	14.0	
418	49.0	6.0	9.0	13.0	13.0	12.0	
173	26.0	9.0	11.0	9.0	10.0	10.0	
229	16.0	88.0	78.0	72.0	78.0	88.0	
426	14.0	83.0	79.0	85.0	75.0	80.0	
237	11.0	81.0	82.0	79.0	83.0	81.0	

	VpW	Position Type
397	1.166667	OffMid
436	1.088235	OffMid
76	1.023810	OffMid
375	0.973684	OffMid
345	1.607143	Offensive
293	1.333333	Offensive
329	1.090909	Offensive
204	1.000000	Offensive
480	0.947368	Offensive
226	2.454545	Defense
342	1.464286	Defense
112	1.454545	Defense
274	1.105263	Defense
175	0.909091	Defense
488	0.800000	Defense
428	0.781250	Defense
166	2.027778	Midfield
114	1.840909	Midfield

```
418  1.772727       Midfield
173  1.650000       Midfield
229  1.260870         Goalie
426  1.035714         Goalie
237  1.023810         Goalie

[23 rows x 59 columns]
```

[44]:

```python
print("Using our new team, we get a team that costs us: ")
print("$",our_team['Wage'].sum())
print("Which gives us a Value of: ")
print(our_team['Value'].sum()," million Euros")
print("Now our 'Overall' score is: ")
print("Our team's mean 'Overall' score is: ", our_team.Overall.mean())
```

```
Using our new team, we get a team that costs us:
$ 416.0
Which gives us a Value of:
526.0  million Euros
Now our 'Overall' score is:
Our team's mean 'Overall' score is:  81.78260869565217
```

Oh no! Our 'Value', 'Overall' and even our cost went down, but we have the right players for the positions! Perhaps we should take into account "starters" and "relief" players, perhaps we could get more granular into positions and formations, develop teams around strategies we might have. Think of what we could do if we had more data such as team performance, full team player data and a subject matter expert to refer to for even more insight. At this point we could examine the traits like "Potential", create new attributes combining Potential and Overall, create an algorithm to maximize an attribute under a certain budget and more! We will stop here though, as this is a homework assignment for a job interview and I don't want to dive any further down the rabbit hole. Thanks for the fun, now I have to get back to working overtime this weekend for my current job!