XGBoost and Shapley Values for Olympics

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The following code makes all plots and images higher resolution.

```
knitr::opts_chunk$set(dpi = 300)
```

This is an exercise to help me get the skills for my research. I tried using XGBoost on the Olympics data. First, we need to install the many packages we need for this. We can use install.packages and then library, but using pacman needs less code to do this and is faster.

```
if (!require("pacman")) install.packages("pacman")

## Loading required package: pacman

pacman::p_load(pacman, rio, tidyverse, xgboost, caTools, ggplot2,
Ckmeans.1d.dp,
               DALEXtra, mlr, caret, DiagrammeR, SHAPforxgboost, rmarkdown,
               skimr)
```

Importing Data

Now, let's import the data and then remove the values that are highly correlated with other values. Then, let's look at the structure of the data. Then, let's look at the top 20 rows. There are too many rows, so they spill over to the next page. The ## represents the row #

```
data <- import("olympicmedals.dta")
data = data %>%
  select(-c(cc, year, lpop, lrgdpepc, sptinc992j_p90p100,
sptinc992j_p99p100))
skimr::skim(data)
```

Data summary

Name	data
Number of rows	204
Number of columns	9
Column type frequency:	
numeric	9
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
sptinc992j_p0p50	33	0.84	0.15	0.04	0.03	0.12	0.15	0.18	0.26	▁▃▇▆▂
rgdpe	28	0.86	712359.86	2368985.23	784.53	27290.08	97008.34	460800.94	20860506.00	▇▁▁▁▁
pop	28	0.86	43.07	153.75	0.03	2.81	9.72	30.77	1433.78	▇▁▁▁▁
avh	138	0.32	1849.98	269.24	1380.61	1650.92	1818.28	2061.05	2474.91	▅▇▇▅▂
hc	61	0.70	2.71	0.71	1.22	2.13	2.77	3.26	4.35	▅▅▇▇▁
rnna	29	0.86	3209645.14	10320354.02	2833.90	91149.59	356459.34	1935716.62	101703024.00	▇▁▁▁▁
LifeLadder	55	0.73	5.51	1.10	2.38	4.74	5.49	6.23	7.89	▁▅▇▇▃
points	0	1.00	10.28	28.75	0.00	0.00	0.00	8.00	232.00	▇▁▁▁▁
rgdpepc	28	0.86	22213.10	22095.72	251.32	5106.27	13933.31	33252.37	112941.45	▇▂▁▁▁

```r
head(data,n = 20)
```

```
##    sptinc992j_p0p50       rgdpe        pop      avh       hc       rnna
## 1                NA    3921.261   0.106314       NA       NA   18427.50
## 2            0.1776          NA         NA       NA       NA         NA
## 3            0.0904  228151.016  31.825295       NA 1.481984 1367457.88
## 4            0.1886   35890.020   2.880917       NA 2.964992  227804.64
## 5                NA          NA         NA       NA       NA         NA
## 6            0.1274  681525.812   9.770529       NA 2.746695 4506529.00
## 7            0.1623  991646.312  44.780677 1609.069 3.096804 3399148.50
## 8            0.1854   41048.629   2.957731       NA 3.135995   98812.77
## 9                NA          NA         NA       NA       NA         NA
## 10               NA    1986.163   0.097118       NA       NA   10993.36
## 11           0.1616 1280843.250  25.203198 1726.798 3.549666 5913514.00
## 12           0.2202  498022.250   8.955102 1611.374 3.381046 2878110.75
## 13           0.2029  162126.188  10.047718       NA       NA  275832.31
## 14           0.1402    8664.988  11.530580       NA 1.416526   18935.97
## 15           0.2040  589449.125  11.539328 1586.431 3.149034 3498440.75
## 16           0.1142   36740.742  11.801151       NA 1.918610   88271.80
## 17           0.1504   43608.875  20.321378       NA 1.286242   86734.51
## 18           0.1706  756355.562 163.046161 2418.883 2.101790 2844179.25
## 19          0.1650  159419.969   7.000119 1645.246 3.186015  456857.28
## 20          0.1014   74097.227   1.641172       NA 2.229507  429310.66
##    LifeLadder points    rgdpepc
## 1          NA      0 36883.7695
## 2    2.375092      0         NA
## 3          NA      0  7168.8579
## 4    5.364910      0 12457.8457
## 5          NA      0         NA
## 6    6.458392      0 69753.2188
## 7    5.900567      4 22144.5137
## 8    5.488087      6 13878.4189
## 9          NA      0         NA
## 10         NA      0 20451.0312
## 11   7.137368     87 50820.6641
## 12   7.213489     10 55613.2422
## 13   5.173389     10 16135.6230
## 14   3.775283      0   751.4789
## 15   6.838761     14 51081.7539
## 16   4.407746      0  3113.3186
## 17   4.740893      1  2145.9604
## 18   5.279987      0  4638.9043
## 19   5.597723     13 22773.8945
## 20   6.173176      2 45148.9727
```

Let's set the same seed for random number generation for reproducibility. Then, let's split the data into a training and testing set. The model will be tested on the training set, and then tested on the testing set for accuracy. 75% of the data is going into the training set, and 25% of the data is going into the testing set.

```
set.seed(1)
split = sample.split(data$points, SplitRatio = 0.75)
training_set = subset(data, split == TRUE)
testing_set = subset(data, split == FALSE)
```

The XGBoost algorithm requires that the input values are in a matrix. The algorithm only accepts numerical data. This also means that if there is categorical variables, we have to change them to dummy variables where each column is either a 0 or 1 depending on the category and there are n - 1 columns to represent the categorical data. In this dataset, there are no categorical values.

Let's change the training and testing sets into a matrix.

```
training_set = training_set %>%
  as.matrix()

testing_set = testing_set %>%
  as.matrix()
```

Model Generation

Let’s make the XGBoost model, predict some new values and calculate the error in terms of MSE, MAE and RMSE on the testing set.

```
model = xgboost(data = training_set[,-8], label = training_set[,8], nrounds =
40)

## [1]  train-rmse:26.374670
## [2]  train-rmse:20.696814
## [3]  train-rmse:16.510298
## [4]  train-rmse:13.157394
## [5]  train-rmse:10.600866
## [6]  train-rmse:8.590517
## [7]  train-rmse:7.086412
## [8]  train-rmse:5.897498
## [9]  train-rmse:4.995760
## [10] train-rmse:4.268226
## [11] train-rmse:3.628120
## [12] train-rmse:3.085234
## [13] train-rmse:2.665470
## [14] train-rmse:2.329151
## [15] train-rmse:2.062102
## [16] train-rmse:1.835249
## [17] train-rmse:1.636155
## [18] train-rmse:1.482885
## [19] train-rmse:1.340541
## [20] train-rmse:1.242759
## [21] train-rmse:1.168821
## [22] train-rmse:1.025638
## [23] train-rmse:0.927718
## [24] train-rmse:0.834716
## [25] train-rmse:0.776352
## [26] train-rmse:0.731941
## [27] train-rmse:0.682258
## [28] train-rmse:0.635137
## [29] train-rmse:0.569089
## [30] train-rmse:0.540080
## [31] train-rmse:0.487153
## [32] train-rmse:0.438523
## [33] train-rmse:0.405070
## [34] train-rmse:0.364107
## [35] train-rmse:0.315020
## [36] train-rmse:0.277065
## [37] train-rmse:0.258927
## [38] train-rmse:0.232593
## [39] train-rmse:0.215684
## [40] train-rmse:0.200511

pred_y = predict(model,testing_set[,-8])
```

```
mse = mean((testing_set[8] - pred_y)^2)
mae = caret::MAE(testing_set[8], pred_y)
rmse = caret::RMSE(testing_set[8], pred_y)

cat("MSE: ", mse, "MAE: ", mae, " RMSE: ", rmse)

## MSE:  32.07732 MAE:  3.330121  RMSE:  5.663685
```

Let's compare this to the initial linear model that I made before.

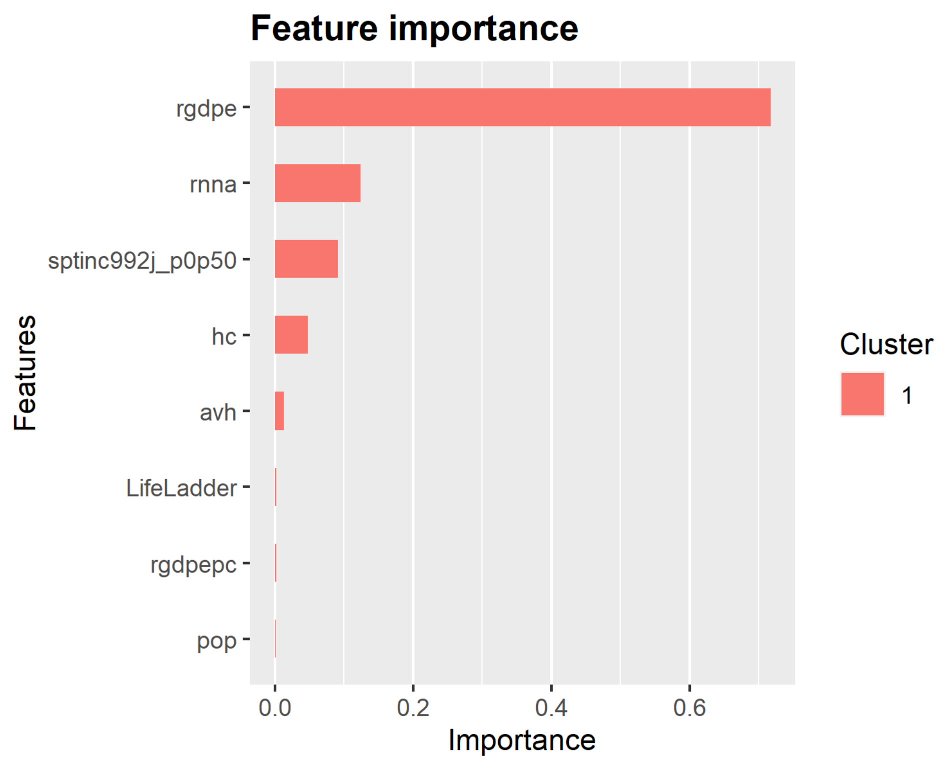
```
data2 <- import("olympicmedals.dta")
data2 <- data2 %>%
  filter(!is.na(data2$lpop))

data2 <- data2 %>%
  filter(!is.na(data2$lrgdpepc))

set.seed(1)
split2 = sample.split(data2$points, SplitRatio = 0.75)
training_set2 = subset(data2, split2 == TRUE)
testing_set2 = subset(data2, split2 == FALSE)

model2 <- lm(points ~ lpop + lrgdpepc, data=training_set2)
pred_y2 = predict(model2,testing_set2[,-12])

mse2 = mean((testing_set2[,12] - pred_y2)^2)
mae2 = caret::MAE(testing_set2[,12], pred_y2)
rmse2 = caret::RMSE(testing_set2[,12], pred_y2)

cat("MSE: ", mse2, "MAE: ", mae2, " RMSE: ", rmse2)

## MSE:  337.4018 MAE:  15.62729  RMSE:  18.3685
```

The XGBoost model is much more accurate. It has an RMSE of 5.66, compared to the linear regression model which has a RMSE of 18.3685.

Visualizing the results

Let's now visualize what features are important in this model. Out of all the variables we supplied to the model, which were the most important?

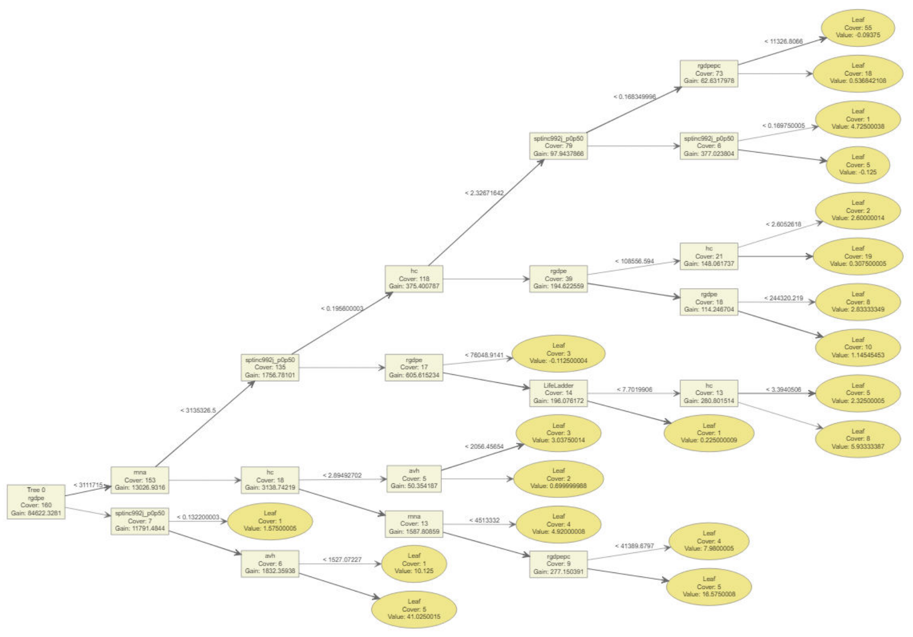
```
xgb_imp <- xgb.importance(feature_names = model$feature_names,
                          model = model)
xgb.ggplot.importance(xgb_imp, n_clusters = 1)
```



It looks like rgdpe (Expenditure-side real GDP at chained PPPs (in mil. 2017 US$) was the most important variable in predicting the results.

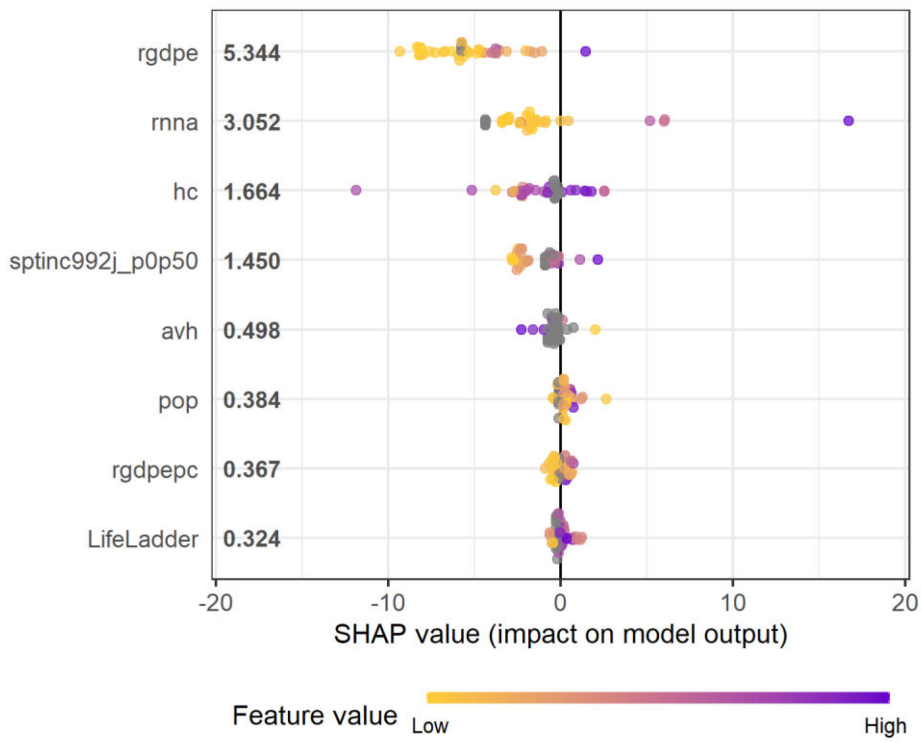
This will plot the first decision tree, which is not really useful for interpretation as XGBoost is an ensemble decision tree model, composed of many trees. However, it is still useful to give us an idea of what the algorithm is thinking about.

```
xgb.plot.tree(model = model, trees = 0)
```


Tree 0 rgdpe Cover: 160 Gain: 84622.3281
< 3111715
rnna Cover: 153 Gain: 13026.9316
sptinc992j_p0p50 Cover: 7 Gain: 11791.4844
< 3135326.5
sptinc992j_p0p50 Cover: 135 Gain: 1756.78101
hc Cover: 18 Gain: 3138.74219
< 0.132200003
Leaf Cover: 1 Value: 1.57500005
avh Cover: 6 Gain: 1832.35938
< 1527.07227
Leaf Cover: 1 Value: 10.125
Leaf Cover: 5 Value: 41.0250015
< 0.195600003
hc Cover: 118 Gain: 375.400787
rgdpe Cover: 17 Gain: 605.615234
< 2.89492702
avh Cover: 5 Gain: 50.354187
rnna Cover: 13 Gain: 1587.80859
< 2.32671642
sptinc992j_p0p50 Cover: 79 Gain: 97.9437866
rgdpe Cover: 39 Gain: 194.622559
< 76048.9141
Leaf Cover: 3 Value: -0.112500004
LifeLadder Cover: 14 Gain: 196.076172
< 2056.45654
Leaf Cover: 3 Value: 3.03750014
Leaf Cover: 2 Value: 0.699999988
< 4513332
Leaf Cover: 4 Value: 4.92000008
rgdpepc Cover: 9 Gain: 277.150391
< 0.168349996
rgdpepc Cover: 73 Gain: 82.6317978
sptinc992j_p0p50 Cover: 6 Gain: 377.023804
< 108556.594
hc Cover: 21 Gain: 148.061737
rgdpe Cover: 18 Gain: 114.246704
< 7.7019906
hc Cover: 13 Gain: 280.801514
Leaf Cover: 1 Value: 0.225000009
< 41389.6797
Leaf Cover: 4 Value: 7.9800005
Leaf Cover: 5 Value: 16.5750008
< 11326.8066
Leaf Cover: 55 Value: -0.09375
Leaf Cover: 18 Value: 0.536842108
< 0.169750005
Leaf Cover: 1 Value: 4.72500038
Leaf Cover: 5 Value: -0.125
< 2.6052618
Leaf Cover: 2 Value: 2.60000014
Leaf Cover: 19 Value: 0.307500005
< 244320.219
Leaf Cover: 8 Value: 2.83333349
Leaf Cover: 10 Value: 1.14545453
< 3.3940506
Leaf Cover: 5 Value: 2.32500005
Leaf Cover: 8 Value: 5.93333387

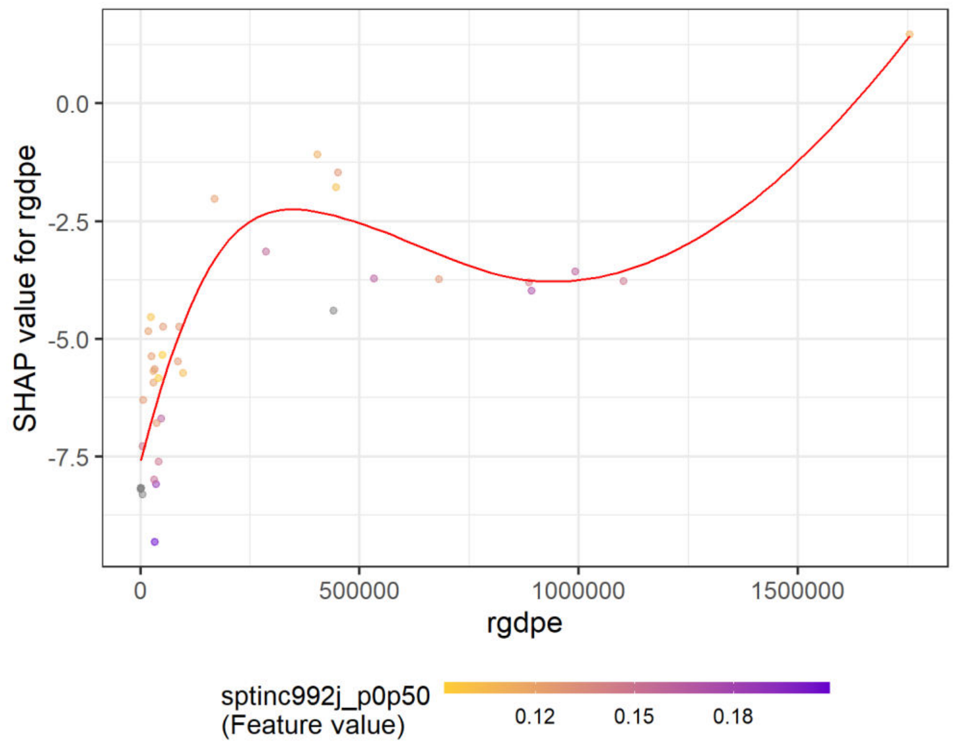
Now let's calculate the SHAP values and see which variable features were most important for our model.

```r
shap <- shap.prep(xgb_model = model, X_train = testing_set[,-8])
shap.plot.summary(shap)
```



Rgdpe is the most important valuable for predicting points won in the olympics. Let's look at this variable in a partial dependence plot.

```r
shap.plot.dependence(shap, "rgdpe", color_feature = "auto",
                     alpha = 0.5, jitter_width = 0.1)

## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 7 rows containing non-finite values (stat_smooth).

## Warning: Removed 7 rows containing missing values (geom_point).
```



It seems that a low rgdpe (Expenditure-side real GDP at chained PPPs (in mil. 2017 US$) hampers your ability to get points at a low value, has less an effect at higher values, and at very high values allows you to obtain higher points. Let us make sure of the results by looking again at our testing set.

```
  max(testing_set[,8])

## [1] 10
```

It seems the country with the maximum amount of points in the testing set was 10. If we compare this to our training set:

```
  max(training_set[,8])

## [1] 232
```

The maximum amount of points of a country in the training set is 232. This is an result of the countries randomly being put in the training and testing set. How do the results differ if a country with higher points was randomly chosen to be in the testing set? Let's try a SplitRatio of 0.7.

```
data <- import("olympicmedals.dta")

data = data %>%
  select(-c(cc, year, lpop, lrgdpepc, sptinc992j_p90p100,
sptinc992j_p99p100))

set.seed(1)
split = sample.split(data$points, SplitRatio = 0.7)
```

```
training_set = subset(data, split == TRUE)
testing_set = subset(data, split == FALSE)

training_set = training_set %>%
  as.matrix()

testing_set = testing_set %>%
  as.matrix()
```

Let's check the testing set to see if it has a higher country with max value for points.

```
  max(testing_set[,8])

## [1] 68
```

Let's also check the max value for points in the training set to see if it includes a high point scoring country.

```
  max(training_set[,8])

## [1] 232
```

Now let's calculate the model again.

```
model = xgboost(data = training_set[,-8], label = training_set[,8], nrounds = 
40)

## [1]  train-rmse:27.064226
## [2]  train-rmse:21.260931
## [3]  train-rmse:17.006104
## [4]  train-rmse:13.642632
## [5]  train-rmse:10.957189
## [6]  train-rmse:8.904371
## [7]  train-rmse:7.340249
## [8]  train-rmse:6.071575
## [9]  train-rmse:5.093059
## [10] train-rmse:4.339937
## [11] train-rmse:3.710795
## [12] train-rmse:3.165035
## [13] train-rmse:2.737292
## [14] train-rmse:2.358058
## [15] train-rmse:2.060940
## [16] train-rmse:1.819282
## [17] train-rmse:1.568922
## [18] train-rmse:1.391671
## [19] train-rmse:1.254977
## [20] train-rmse:1.144986
## [21] train-rmse:0.995366
## [22] train-rmse:0.869612
## [23] train-rmse:0.750286
## [24] train-rmse:0.683142
## [25] train-rmse:0.635431
## [26] train-rmse:0.596431
## [27] train-rmse:0.561876
## [28] train-rmse:0.494441
## [29] train-rmse:0.451951
## [30] train-rmse:0.425904
## [31] train-rmse:0.397457
## [32] train-rmse:0.375684
## [33] train-rmse:0.330268
## [34] train-rmse:0.319064
## [35] train-rmse:0.286340
## [36] train-rmse:0.274272
## [37] train-rmse:0.263440
## [38] train-rmse:0.257379
## [39] train-rmse:0.232242
## [40] train-rmse:0.210472
```

```
pred_y = predict(model,testing_set[,-8])


mse = mean((testing_set[8] - pred_y)^2)
mae = caret::MAE(testing_set[8], pred_y)
rmse = caret::RMSE(testing_set[8], pred_y)

cat("MSE: ", mse, "MAE: ", mae, " RMSE: ", rmse)
```

```
## MSE:  374.9142 MAE:  7.262226  RMSE:  19.3627
```

The RMSE of our model is now 19.36, larger than the RMSE for our linear model at 18.37. At smaller values of points, the XGBoost model works better than the linear model. However, at larger values of points, the XGboost model becomes worse than the linear model. Only a few countries won a lot of points in the olympics (USA, Russia, Great Britain, Japan and China). This is probably because of insufficient data - XGBoost is designed for very large data, and does not work well with a few outliers in a very small dataset.