

Exploratory data analysis - violence in the world and woman grand master likelihood.

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In this project we are going to analyze to different set of data, and see what they tell us about the likelihood of a woman grandmaster chess appearing and how it relates to violence against women in said country, this will imply a huge amount of data cleaning and interpretation before arriving to a relevant correlation. We expect in advance and acknowledge that other variables such as economic variables per country may correlate more strongly to both violence and women grandmaster players.

We may also use the term grandmaster interchangeably with just the women top player, this is both a practicality and an intentional way to recognize women in countries were grandmasters are less likely to appear but still have top ranked players.

The next block is the setup script to load data, and setup this notebook utilities.

```
chooseCRANmirror(ind = 52)
# EDA & Kaggle auth packages
install.packages(c("summarytools", "explore", "dataMaid", "devtools", "configr", "rsconnect", "dplyr"))

##
## The downloaded binary packages are in
## /var/folders/f3/2p9snhhj759g511f2ztjbwdw0000gn/T//Rtmpjf0tRQ/downloaded_packages

devtools::install_github("ldurazo/kaggler")

## Skipping install of 'kaggler' from a github remote, the SHA1 (bfb8fb69) has not changed since last i
## Use 'force = TRUE' to force installation

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
## filter, lag

## The following objects are masked from 'package:base':
##
## intersect, setdiff, setequal, union
```

```
library(summarytools)
```

```
## Registered S3 method overwritten by 'pryr':  
##   method      from  
##   print.bytes Rcpp
```

```
## For best results, restart R session and update pander using devtools:: or remotes::install_github('r')
```

```
library(explore)  
library(dataMaid)
```

```
##  
## Attaching package: 'dataMaid'
```

```
## The following object is masked from 'package:dplyr':  
##  
##   summarize
```

```
library(configr)  
library(readr)  
library(rsconnect)  
library(kagglr)
```

```
# files downloading  
kgl_auth(creds_file = 'kaggle.json')
```

```
## <request>  
## Options:  
## * httpauth: 1  
## * userpwd: ldurazo:48ce1a6f4b7269d4b6f8ce2d3b854199
```

```
response_violence <- kgl_datasets_download_all(owner_dataset = "andrewmvd/violence-against-women-and-gi  
download.file(response_violence[["url"]], "data/violence_temp.zip", mode = "wb")  
unzipResult <- unzip("data/violence_temp.zip", exdir = "data/", overwrite = TRUE)
```

```
## Warning in unzip("data/violence_temp.zip", exdir = "data/", overwrite = TRUE):  
## error -1 al extraer del archivo zip
```

```
violence_data <- read_csv("data/makeovermonday-2020w10/violence_data.csv")
```

```
##  
## -- Column specification -----  
## cols(  
##   RecordID = col_double(),  
##   Country = col_character(),  
##   Gender = col_character(),  
##   'Demographics Question' = col_character(),  
##   'Demographics Response' = col_character(),  
##   Question = col_character(),  
##   'Survey Year' = col_character(),  
##   Value = col_double()  
## )
```

```
## Warning: 1 parsing failure.
##   row col  expected    actual                                file
## 11354 -- 8 columns 6 columns 'data/makeovermonday-2020w10/violence_data.csv'
```

```
response_chessplayers <- kgl_datasets_download_all(owner_dataset = "vikasojha98/top-women-chess-players
download.file(response_chessplayers[["url"]], "data/chess_temp.zip", mode = "wb")
unzipResult <- unzip("data/chess_temp.zip", exdir = "data/", overwrite = TRUE)
```

```
## Warning in unzip("data/chess_temp.zip", exdir = "data/", overwrite = TRUE):
## error -1 al extraer del archivo zip
```

```
chess_data <- read_csv("data/top_women_chess_players_aug_2020.csv")
```

```
##
## -- Column specification -----
## cols(
##   'Fide id' = col_double(),
##   Name = col_character(),
##   Federation = col_character(),
##   Gender = col_logical(),
##   Year_of_birth = col_double(),
##   Title = col_character(),
##   Standard_Rating = col_double(),
##   Rapid_rating = col_double(),
##   Blitz_rating = col_double(),
##   Inactive_flag = col_character()
## )
```

With these two files we can now see a summary of the data. Note that these two are html generated files available if you run this notebook. Alternatively, the explore package returns interesting results in a shiny app, turn the following statements on if you want to see the data.

```
#dfSummary(violence_data, file = "data/violence_data_summary.html")
#dfSummary(chess_data, file = "data/violence_data_summary.html")

#explore(chess_data)
#explore(violence_data)
```

We will need a file that maps the ISO-3166 country alpha 3 on the chess data, to the country name in violence data.

```
download.file("https://raw.githubusercontent.com/luke/ISO-3166-Countries-with-Regional-Codes/master/al
countries_mapping <- read_csv("data/iso-3166")
```

```
##
## -- Column specification -----
## cols(
##   name = col_character(),
##   'alpha-2' = col_character(),
##   'alpha-3' = col_character(),
##   'country-code' = col_character(),
```

```
## 'iso_3166-2' = col_character(),
## region = col_character(),
## 'sub-region' = col_character(),
## 'intermediate-region' = col_character(),
## 'region-code' = col_character(),
## 'sub-region-code' = col_character(),
## 'intermediate-region-code' = col_character()
## )
```

```
countries_mapping <- setNames(select(countries_mapping, "name", "alpha-3"), c("name", "code"))
print(countries_mapping)
```

```
## # A tibble: 249 x 2
##   name                code
##   <chr>              <chr>
## 1 Afghanistan      AFG
## 2 Åland Islands    ALA
## 3 Albania           ALB
## 4 Algeria           DZA
## 5 American Samoa   ASM
## 6 Andorra           AND
## 7 Angola            AGO
## 8 Anguilla          AIA
## 9 Antarctica       ATA
## 10 Antigua and Barbuda ATG
## # ... with 239 more rows
```

Let's clean up our data by removing the NA values and transforming the percentage to a number.

```
violence_data <- na.omit(violence_data, "Value")
violence_data$Value <- as.numeric(sub("%", "", violence_data$Value))
```

Now I want to create an aggregate of the data of my first data set of violence against women, and generate a weighted mean out of the results between men and women answering, so that I can effectively create a “violence score” per country, in a very subjective way. There are a number of better techniques to do such a process, but only for the sake of the exercise we will use this score formula.

```
violence_data$WeightedValue <- ifelse(violence_data$Gender == "F", violence_data$Value * 0.7, violence_data$Value * 0.3)
violence_data_slim <- select(violence_data, "Country", "WeightedValue")
violence_data_slim_grouped <- setNames(aggregate(violence_data_slim$WeightedValue, by = list(violence_data_slim$Country), FUN = mean), c("Country", "Score"))
print(violence_data_slim_grouped)
```

```
##           Country      Score
## 1  Afghanistan 22.5288095
## 2    Albania   2.4524444
## 3    Angola    7.0797778
## 4    Armenia   4.0113095
## 5  Azerbaijan 16.7045833
## 6  Bangladesh 10.3033333
## 7     Benin    7.8707778
## 8    Bolivia   5.3954444
```

## 9	Burkina Faso	10.8768889
## 10	Burundi	15.9398889
## 11	Cambodia	11.2942222
## 12	Cameroon	11.9049444
## 13	Chad	23.4807778
## 14	Colombia	1.1404444
## 15	Comoros	9.5546111
## 16	Congo	19.1671667
## 17	Congo Democratic Republic	22.1008333
## 18	Cote d'Ivoire	13.1191111
## 19	Dominican Republic	0.7340476
## 20	Egypt	15.1758333
## 21	Eritrea	32.3306667
## 22	Eswatini	5.8334444
## 23	Ethiopia	16.6565556
## 24	Gabon	12.3352778
## 25	Gambia	14.8097222
## 26	Ghana	7.0600000
## 27	Guatemala	2.3038333
## 28	Guinea	21.2895000
## 29	Guyana	4.2798889
## 30	Haiti	3.5145000
## 31	Honduras	3.0452778
## 32	India	12.5360556
## 33	Indonesia	7.5503571
## 34	Jordan	5.6417778
## 35	Kenya	11.3071111
## 36	Kyrgyz Republic	10.6180247
## 37	Lesotho	8.9674444
## 38	Liberia	10.6376111
## 39	Madagascar	8.1401667
## 40	Malawi	3.6356111
## 41	Maldives	6.1069167
## 42	Mali	22.4886667
## 43	Moldova	5.4929012
## 44	Morocco	31.6493333
## 45	Mozambique	3.5043333
## 46	Myanmar	11.9392222
## 47	Namibia	7.3674444
## 48	Nepal	6.4663889
## 49	Nicaragua	4.6332222
## 50	Niger	17.0797778
## 51	Nigeria	10.1447778
## 52	Pakistan	13.1031548
## 53	Peru	1.2701111
## 54	Philippines	3.5443333
## 55	Rwanda	9.1943889
## 56	Sao Tome and Principe	5.3686782
## 57	Senegal	13.2816667
## 58	Sierra Leone	16.9027778
## 59	South Africa	1.6648851
## 60	Tajikistan	31.0131111
## 61	Tanzania	16.2912222
## 62	Timor-Leste	24.9147778

```
## 63                Togo  7.3982222
## 64                Turkey 4.2592308
```

With the score per country done, we need to do similar work with the chess players data frame.

```
chess_data <- na.omit(chess_data, "Standard_Rating", "Rapid_rating", "Blitz_rating")
chess_data_slim <- select(chess_data, "Federation", "Standard_Rating", "Rapid_rating", "Blitz_rating")
chess_data_slim_grouped <- chess_data_slim %>%
  group_by(chess_data_slim$Federation) %>%
  summarise(across(ends_with("rating"), list(mean = mean, n = length, max = max, min = min)))
```

```
## 'summarise()' ungrouping output (override with '.groups' argument)
```

```
print(chess_data_slim_grouped)
```

```
## # A tibble: 81 x 13
##   'chess_data_sli~ Standard_Rating~ Standard_Rating~ Standard_Rating~
##   <chr>                <dbl>                <int>                <dbl>
## 1 ALB                  1971                  1                  1971
## 2 ALG                  1900                  1                  1900
## 3 ARG                  1930.                  2                  1940
## 4 ARM                  2285                  1                  2285
## 5 AUS                  1926.                  4                  2062
## 6 AUT                  1975                  1                  1975
## 7 AZE                  2103.                  8                  2279
## 8 BAN                  2049                  2                  2114
## 9 BEL                  2136                  2                  2258
## 10 BIH                 2025                  1                  2025
## # ... with 71 more rows, and 9 more variables: Standard_Rating_min <dbl>,
## #   Rapid_rating_mean <dbl>, Rapid_rating_n <int>, Rapid_rating_max <dbl>,
## #   Rapid_rating_min <dbl>, Blitz_rating_mean <dbl>, Blitz_rating_n <int>,
## #   Blitz_rating_max <dbl>, Blitz_rating_min <dbl>
```

Now, we need to join the tables with the countries table in order to finally obtain a single dataset.

```
violence_df <- left_join(violence_data_slim_grouped, countries_mapping, by = c("Country" = "name"))
print(violence_df)
```

```
##           Country      Score code
## 1  Afghanistan 22.5288095  AFG
## 2    Albania  2.4524444  ALB
## 3    Angola  7.0797778  AGO
## 4    Armenia  4.0113095  ARM
## 5  Azerbaijan 16.7045833  AZE
## 6  Bangladesh 10.3033333  BGD
## 7    Benin  7.8707778  BEN
## 8    Bolivia  5.3954444 <NA>
## 9  Burkina Faso 10.8768889  BFA
## 10   Burundi 15.9398889  BDI
## 11   Cambodia 11.2942222  KHM
## 12   Cameroon 11.9049444  CMR
```

## 13	Chad	23.4807778	TCD
## 14	Colombia	1.1404444	COL
## 15	Comoros	9.5546111	COM
## 16	Congo	19.1671667	COG
## 17	Congo Democratic Republic	22.1008333	<NA>
## 18	Cote d'Ivoire	13.1191111	<NA>
## 19	Dominican Republic	0.7340476	DOM
## 20	Egypt	15.1758333	EGY
## 21	Eritrea	32.3306667	ERI
## 22	Eswatini	5.8334444	SWZ
## 23	Ethiopia	16.6565556	ETH
## 24	Gabon	12.3352778	GAB
## 25	Gambia	14.8097222	GMB
## 26	Ghana	7.0600000	GHA
## 27	Guatemala	2.3038333	GTM
## 28	Guinea	21.2895000	GIN
## 29	Guyana	4.2798889	GUY
## 30	Haiti	3.5145000	HTI
## 31	Honduras	3.0452778	HND
## 32	India	12.5360556	IND
## 33	Indonesia	7.5503571	IDN
## 34	Jordan	5.6417778	JOR
## 35	Kenya	11.3071111	KEN
## 36	Kyrgyz Republic	10.6180247	<NA>
## 37	Lesotho	8.9674444	LSO
## 38	Liberia	10.6376111	LBR
## 39	Madagascar	8.1401667	MDG
## 40	Malawi	3.6356111	MWI
## 41	Maldives	6.1069167	MDV
## 42	Mali	22.4886667	MLI
## 43	Moldova	5.4929012	<NA>
## 44	Morocco	31.6493333	MAR
## 45	Mozambique	3.5043333	MOZ
## 46	Myanmar	11.9392222	MMR
## 47	Namibia	7.3674444	NAM
## 48	Nepal	6.4663889	NPL
## 49	Nicaragua	4.6332222	NIC
## 50	Niger	17.0797778	NER
## 51	Nigeria	10.1447778	NGA
## 52	Pakistan	13.1031548	PAK
## 53	Peru	1.2701111	PER
## 54	Philippines	3.5443333	PHL
## 55	Rwanda	9.1943889	RWA
## 56	Sao Tome and Principe	5.3686782	STP
## 57	Senegal	13.2816667	SEN
## 58	Sierra Leone	16.9027778	SLE
## 59	South Africa	1.6648851	ZAF
## 60	Tajikistan	31.0131111	TJK
## 61	Tanzania	16.2912222	<NA>
## 62	Timor-Leste	24.9147778	TLS
## 63	Togo	7.3982222	TGO
## 64	Turkey	4.2592308	TUR

Notice that we have a few exemptions where the mapping did not occur correctly, in this instance we will

fix them by hand. - Bolivia - Congo Democratic Republic - Cote d'Ivoire - Kyrgyz Republic - Moldova - Tanzania

```
violence_df <- within(violence_df, code[Country == "Bolivia"] <- "BOL")
violence_df <- within(violence_df, code[Country == "Congo Democratic Republic"] <- "COD")
violence_df <- within(violence_df, code[Country == "Cote d'Ivoire"] <- "CIV")
violence_df <- within(violence_df, code[Country == "Kyrgyz Republic"] <- "KGZ")
violence_df <- within(violence_df, code[Country == "Moldova"] <- "MDA")
violence_df <- within(violence_df, code[Country == "Tanzania"] <- "TZA")
violence_df %>% arrange(!is.na(violence_df$code))
```

##	Country	Score	code
## 1	Afghanistan	22.5288095	AFG
## 2	Albania	2.4524444	ALB
## 3	Angola	7.0797778	AGO
## 4	Armenia	4.0113095	ARM
## 5	Azerbaijan	16.7045833	AZE
## 6	Bangladesh	10.3033333	BGD
## 7	Benin	7.8707778	BEN
## 8	Bolivia	5.3954444	BOL
## 9	Burkina Faso	10.8768889	BFA
## 10	Burundi	15.9398889	BDI
## 11	Cambodia	11.2942222	KHM
## 12	Cameroon	11.9049444	CMR
## 13	Chad	23.4807778	TCD
## 14	Colombia	1.1404444	COL
## 15	Comoros	9.5546111	COM
## 16	Congo	19.1671667	COG
## 17	Congo Democratic Republic	22.1008333	COD
## 18	Cote d'Ivoire	13.1191111	CIV
## 19	Dominican Republic	0.7340476	DOM
## 20	Egypt	15.1758333	EGY
## 21	Eritrea	32.3306667	ERI
## 22	Eswatini	5.8334444	SWZ
## 23	Ethiopia	16.6565556	ETH
## 24	Gabon	12.3352778	GAB
## 25	Gambia	14.8097222	GMB
## 26	Ghana	7.0600000	GHA
## 27	Guatemala	2.3038333	GTM
## 28	Guinea	21.2895000	GIN
## 29	Guyana	4.2798889	GUY
## 30	Haiti	3.5145000	HTI
## 31	Honduras	3.0452778	HND
## 32	India	12.5360556	IND
## 33	Indonesia	7.5503571	IDN
## 34	Jordan	5.6417778	JOR
## 35	Kenya	11.3071111	KEN
## 36	Kyrgyz Republic	10.6180247	KGZ
## 37	Lesotho	8.9674444	LSO
## 38	Liberia	10.6376111	LBR
## 39	Madagascar	8.1401667	MDG
## 40	Malawi	3.6356111	MWI
## 41	Maldives	6.1069167	MDV
## 42	Mali	22.4886667	MLI


```
## 43          Moldova  5.4929012  MDA
## 44          Morocco 31.6493333  MAR
## 45      Mozambique  3.5043333  MOZ
## 46          Myanmar 11.9392222  MMR
## 47          Namibia  7.3674444  NAM
## 48          Nepal   6.4663889  NPL
## 49      Nicaragua  4.6332222  NIC
## 50          Niger   17.0797778  NER
## 51          Nigeria 10.1447778  NGA
## 52      Pakistan   13.1031548  PAK
## 53          Peru    1.2701111  PER
## 54      Philippines 3.5443333  PHL
## 55          Rwanda  9.1943889  RWA
## 56      Sao Tome and Principe 5.3686782  STP
## 57          Senegal 13.2816667  SEN
## 58      Sierra Leone 16.9027778  SLE
## 59      South Africa 1.6648851  ZAF
## 60      Tajikistan  31.0131111  TJK
## 61      Tanzania   16.2912222  TZA
## 62      Timor-Leste 24.9147778  TLS
## 63          Togo    7.3982222  TGO
## 64          Turkey  4.2592308  TUR
```

```
print(violence_df)
```

```
##          Country      Score code
## 1      Afghanistan 22.5288095  AFG
## 2          Albania  2.4524444  ALB
## 3          Angola   7.0797778  AGO
## 4          Armenia  4.0113095  ARM
## 5      Azerbaijan 16.7045833  AZE
## 6      Bangladesh 10.3033333  BGD
## 7          Benin    7.8707778  BEN
## 8          Bolivia  5.3954444  BOL
## 9      Burkina Faso 10.8768889  BFA
## 10         Burundi 15.9398889  BDI
## 11         Cambodia 11.2942222  KHM
## 12         Cameroon 11.9049444  CMR
## 13          Chad    23.4807778  TCD
## 14         Colombia  1.1404444  COL
## 15         Comoros  9.5546111  COM
## 16          Congo   19.1671667  COG
## 17 Congo Democratic Republic 22.1008333  COD
## 18         Cote d'Ivoire 13.1191111  CIV
## 19      Dominican Republic  0.7340476  DOM
## 20          Egypt   15.1758333  EGY
## 21          Eritrea 32.3306667  ERI
## 22         Eswatini  5.8334444  SWZ
## 23         Ethiopia 16.6565556  ETH
## 24          Gabon   12.3352778  GAB
## 25         Gambia   14.8097222  GMB
## 26          Ghana    7.0600000  GHA
## 27         Guatemala 2.3038333  GTM
## 28          Guinea  21.2895000  GIN
```

## 29	Guyana	4.2798889	GUY
## 30	Haiti	3.5145000	HTI
## 31	Honduras	3.0452778	HND
## 32	India	12.5360556	IND
## 33	Indonesia	7.5503571	IDN
## 34	Jordan	5.6417778	JOR
## 35	Kenya	11.3071111	KEN
## 36	Kyrgyz Republic	10.6180247	KGZ
## 37	Lesotho	8.9674444	LSO
## 38	Liberia	10.6376111	LBR
## 39	Madagascar	8.1401667	MDG
## 40	Malawi	3.6356111	MWI
## 41	Maldives	6.1069167	MDV
## 42	Mali	22.4886667	MLI
## 43	Moldova	5.4929012	MDA
## 44	Morocco	31.6493333	MAR
## 45	Mozambique	3.5043333	MOZ
## 46	Myanmar	11.9392222	MMR
## 47	Namibia	7.3674444	NAM
## 48	Nepal	6.4663889	NPL
## 49	Nicaragua	4.6332222	NIC
## 50	Niger	17.0797778	NER
## 51	Nigeria	10.1447778	NGA
## 52	Pakistan	13.1031548	PAK
## 53	Peru	1.2701111	PER
## 54	Philippines	3.5443333	PHL
## 55	Rwanda	9.1943889	RWA
## 56	Sao Tome and Principe	5.3686782	STP
## 57	Senegal	13.2816667	SEN
## 58	Sierra Leone	16.9027778	SLE
## 59	South Africa	1.6648851	ZAF
## 60	Tajikistan	31.0131111	TJK
## 61	Tanzania	16.2912222	TZA
## 62	Timor-Leste	24.9147778	TLS
## 63	Togo	7.3982222	TGO
## 64	Turkey	4.2592308	TUR

Now, assuming the FIDE and ISO-3166 codes are the same, let's see how the joined data looks like. Because the countries that have women chess players may not intersect with the countries visited for questionnaire in the violence dataset, I expect plenty of this missed intersections to have NA values. For this analysis we will pay closer attention to the violence score aggregation, and see which countries have top chess players rather than joining all countries in the FIDE and ignore violence score for countries that do not have chess players.

```
merged_df <- left_join(violence_df, chess_data_slim_grouped, by = c("code" = "chess_data_slim$Federation
print(merged_df)
```

##	Country	Score	code	Standard_Rating_mean
## 1	Afghanistan	22.5288095	AFG	NA
## 2	Albania	2.4524444	ALB	1971.000
## 3	Angola	7.0797778	AGO	NA
## 4	Armenia	4.0113095	ARM	2285.000
## 5	Azerbaijan	16.7045833	AZE	2103.375

## 6	Bangladesh	10.3033333	BGD	NA
## 7	Benin	7.8707778	BEN	NA
## 8	Bolivia	5.3954444	BOL	1888.000
## 9	Burkina Faso	10.8768889	BFA	NA
## 10	Burundi	15.9398889	BDI	NA
## 11	Cambodia	11.2942222	KHM	NA
## 12	Cameroon	11.9049444	CMR	NA
## 13	Chad	23.4807778	TCD	NA
## 14	Colombia	1.1404444	COL	2001.875
## 15	Comoros	9.5546111	COM	NA
## 16	Congo	19.1671667	COG	NA
## 17	Congo Democratic Republic	22.1008333	COD	NA
## 18	Cote d'Ivoire	13.1191111	CIV	NA
## 19	Dominican Republic	0.7340476	DOM	NA
## 20	Egypt	15.1758333	EGY	1995.000
## 21	Eritrea	32.3306667	ERI	NA
## 22	Eswatini	5.8334444	SWZ	NA
## 23	Ethiopia	16.6565556	ETH	NA
## 24	Gabon	12.3352778	GAB	NA
## 25	Gambia	14.8097222	GMB	NA
## 26	Ghana	7.0600000	GHA	NA
## 27	Guatemala	2.3038333	GTM	NA
## 28	Guinea	21.2895000	GIN	NA
## 29	Guyana	4.2798889	GUY	NA
## 30	Haiti	3.5145000	HTI	NA
## 31	Honduras	3.0452778	HND	NA
## 32	India	12.5360556	IND	2086.143
## 33	Indonesia	7.5503571	IDN	NA
## 34	Jordan	5.6417778	JOR	1964.000
## 35	Kenya	11.3071111	KEN	NA
## 36	Kyrgyz Republic	10.6180247	KGZ	NA
## 37	Lesotho	8.9674444	LSO	NA
## 38	Liberia	10.6376111	LBR	NA
## 39	Madagascar	8.1401667	MDG	NA
## 40	Malawi	3.6356111	MWI	NA
## 41	Maldives	6.1069167	MDV	NA
## 42	Mali	22.4886667	MLI	NA
## 43	Moldova	5.4929012	MDA	2161.000
## 44	Morocco	31.6493333	MAR	1853.000
## 45	Mozambique	3.5043333	MOZ	NA
## 46	Myanmar	11.9392222	MMR	NA
## 47	Namibia	7.3674444	NAM	NA
## 48	Nepal	6.4663889	NPL	NA
## 49	Nicaragua	4.6332222	NIC	NA
## 50	Niger	17.0797778	NER	NA
## 51	Nigeria	10.1447778	NGA	NA
## 52	Pakistan	13.1031548	PAK	NA
## 53	Peru	1.2701111	PER	2158.500
## 54	Philippines	3.5443333	PHL	NA
## 55	Rwanda	9.1943889	RWA	NA
## 56	Sao Tome and Principe	5.3686782	STP	NA
## 57	Senegal	13.2816667	SEN	NA
## 58	Sierra Leone	16.9027778	SLE	NA
## 59	South Africa	1.6648851	ZAF	NA

## 60	Tajikistan	31.0131111	TJK	NA
## 61	Tanzania	16.2912222	TZA	NA
## 62	Timor-Leste	24.9147778	TLS	NA
## 63	Togo	7.3982222	TGO	NA
## 64	Turkey	4.2592308	TUR	1940.667
##	Standard_Rating_n	Standard_Rating_max	Standard_Rating_min	Rapid_rating_mean
## 1	NA	NA	NA	NA
## 2	1	1971	1971	1788.000
## 3	NA	NA	NA	NA
## 4	1	2285	2285	2282.000
## 5	8	2279	1871	1950.000
## 6	NA	NA	NA	NA
## 7	NA	NA	NA	NA
## 8	1	1888	1888	1931.000
## 9	NA	NA	NA	NA
## 10	NA	NA	NA	NA
## 11	NA	NA	NA	NA
## 12	NA	NA	NA	NA
## 13	NA	NA	NA	NA
## 14	8	2257	1817	2031.000
## 15	NA	NA	NA	NA
## 16	NA	NA	NA	NA
## 17	NA	NA	NA	NA
## 18	NA	NA	NA	NA
## 19	NA	NA	NA	NA
## 20	4	2182	1832	1895.250
## 21	NA	NA	NA	NA
## 22	NA	NA	NA	NA
## 23	NA	NA	NA	NA
## 24	NA	NA	NA	NA
## 25	NA	NA	NA	NA
## 26	NA	NA	NA	NA
## 27	NA	NA	NA	NA
## 28	NA	NA	NA	NA
## 29	NA	NA	NA	NA
## 30	NA	NA	NA	NA
## 31	NA	NA	NA	NA
## 32	7	2202	1888	1878.714
## 33	NA	NA	NA	NA
## 34	1	1964	1964	1941.000
## 35	NA	NA	NA	NA
## 36	NA	NA	NA	NA
## 37	NA	NA	NA	NA
## 38	NA	NA	NA	NA
## 39	NA	NA	NA	NA
## 40	NA	NA	NA	NA
## 41	NA	NA	NA	NA
## 42	NA	NA	NA	NA
## 43	1	2161	2161	2121.000
## 44	1	1853	1853	1788.000
## 45	NA	NA	NA	NA
## 46	NA	NA	NA	NA
## 47	NA	NA	NA	NA
## 48	NA	NA	NA	NA

## 49	NA	NA	NA	NA
## 50	NA	NA	NA	NA
## 51	NA	NA	NA	NA
## 52	NA	NA	NA	NA
## 53	2	2244	2073	2126.500
## 54	NA	NA	NA	NA
## 55	NA	NA	NA	NA
## 56	NA	NA	NA	NA
## 57	NA	NA	NA	NA
## 58	NA	NA	NA	NA
## 59	NA	NA	NA	NA
## 60	NA	NA	NA	NA
## 61	NA	NA	NA	NA
## 62	NA	NA	NA	NA
## 63	NA	NA	NA	NA
## 64	3	2033	1839	1931.333
##	Rapid_rating_n	Rapid_rating_max	Rapid_rating_min	Blitz_rating_mean
## 1	NA	NA	NA	NA
## 2	1	1788	1788	1886.000
## 3	NA	NA	NA	NA
## 4	1	2282	2282	2275.000
## 5	8	2144	1623	1953.750
## 6	NA	NA	NA	NA
## 7	NA	NA	NA	NA
## 8	1	1931	1931	2020.000
## 9	NA	NA	NA	NA
## 10	NA	NA	NA	NA
## 11	NA	NA	NA	NA
## 12	NA	NA	NA	NA
## 13	NA	NA	NA	NA
## 14	8	2312	1784	2003.250
## 15	NA	NA	NA	NA
## 16	NA	NA	NA	NA
## 17	NA	NA	NA	NA
## 18	NA	NA	NA	NA
## 19	NA	NA	NA	NA
## 20	4	2139	1664	1883.000
## 21	NA	NA	NA	NA
## 22	NA	NA	NA	NA
## 23	NA	NA	NA	NA
## 24	NA	NA	NA	NA
## 25	NA	NA	NA	NA
## 26	NA	NA	NA	NA
## 27	NA	NA	NA	NA
## 28	NA	NA	NA	NA
## 29	NA	NA	NA	NA
## 30	NA	NA	NA	NA
## 31	NA	NA	NA	NA
## 32	7	2075	1569	1907.286
## 33	NA	NA	NA	NA
## 34	1	1941	1941	1857.000
## 35	NA	NA	NA	NA
## 36	NA	NA	NA	NA
## 37	NA	NA	NA	NA

## 38	NA	NA	NA	NA
## 39	NA	NA	NA	NA
## 40	NA	NA	NA	NA
## 41	NA	NA	NA	NA
## 42	NA	NA	NA	NA
## 43	1	2121	2121	2123.000
## 44	1	1788	1788	1769.000
## 45	NA	NA	NA	NA
## 46	NA	NA	NA	NA
## 47	NA	NA	NA	NA
## 48	NA	NA	NA	NA
## 49	NA	NA	NA	NA
## 50	NA	NA	NA	NA
## 51	NA	NA	NA	NA
## 52	NA	NA	NA	NA
## 53	2	2204	2049	2108.000
## 54	NA	NA	NA	NA
## 55	NA	NA	NA	NA
## 56	NA	NA	NA	NA
## 57	NA	NA	NA	NA
## 58	NA	NA	NA	NA
## 59	NA	NA	NA	NA
## 60	NA	NA	NA	NA
## 61	NA	NA	NA	NA
## 62	NA	NA	NA	NA
## 63	NA	NA	NA	NA
## 64	3	2016	1802	1987.333
##	Blitz_rating_n	Blitz_rating_max	Blitz_rating_min	
## 1	NA	NA	NA	
## 2	1	1886	1886	
## 3	NA	NA	NA	
## 4	1	2275	2275	
## 5	8	2109	1656	
## 6	NA	NA	NA	
## 7	NA	NA	NA	
## 8	1	2020	2020	
## 9	NA	NA	NA	
## 10	NA	NA	NA	
## 11	NA	NA	NA	
## 12	NA	NA	NA	
## 13	NA	NA	NA	
## 14	8	2240	1791	
## 15	NA	NA	NA	
## 16	NA	NA	NA	
## 17	NA	NA	NA	
## 18	NA	NA	NA	
## 19	NA	NA	NA	
## 20	4	2072	1698	
## 21	NA	NA	NA	
## 22	NA	NA	NA	
## 23	NA	NA	NA	
## 24	NA	NA	NA	
## 25	NA	NA	NA	
## 26	NA	NA	NA	

## 27	NA	NA	NA
## 28	NA	NA	NA
## 29	NA	NA	NA
## 30	NA	NA	NA
## 31	NA	NA	NA
## 32	7	2076	1619
## 33	NA	NA	NA
## 34	1	1857	1857
## 35	NA	NA	NA
## 36	NA	NA	NA
## 37	NA	NA	NA
## 38	NA	NA	NA
## 39	NA	NA	NA
## 40	NA	NA	NA
## 41	NA	NA	NA
## 42	NA	NA	NA
## 43	1	2123	2123
## 44	1	1769	1769
## 45	NA	NA	NA
## 46	NA	NA	NA
## 47	NA	NA	NA
## 48	NA	NA	NA
## 49	NA	NA	NA
## 50	NA	NA	NA
## 51	NA	NA	NA
## 52	NA	NA	NA
## 53	2	2168	2048
## 54	NA	NA	NA
## 55	NA	NA	NA
## 56	NA	NA	NA
## 57	NA	NA	NA
## 58	NA	NA	NA
## 59	NA	NA	NA
## 60	NA	NA	NA
## 61	NA	NA	NA
## 62	NA	NA	NA
## 63	NA	NA	NA
## 64	3	2026	1933