An Exploratory Analysis of Corruption and Parking Violations

Kenneth Chen, Shiraz Chakraverty, Praba Santhanakrishnan

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Introduction

In this lab assignment, we have access to a unique social experiment to understand relationships between culture and corruption. We define these concepts here and then provide the operational definition to guide our measurements. Our goal is to perform basic exploratory data analysis, based on the following constructs,

1. Every region and country has some form of corruption, a prevailing diplomatic relationship with the UN and by extention, The United States.

2 Diplomatic attitudes are tuned into the following:

+ Economic development of nation.

+ Current world events, how they effect their nation.

+ Level of crime in nation

+ Population of nation, per capita income and crime index.

3. The Clinton-Schumer amendment of October 2002 happens about 13 months after WTC terrorist attacks. This change is visible in the dataset as pre and post records,gives a numerical measure of effects of enforcement.

We are motivated to identify strong relationships between various factors (independent variables) and voilations (dependent variable).Ultimately the construct we want to evaluate is the effect of diplomatic culture, aid and economic metrics, population, corruption and parking violations. We would like to explore relationships there variables have to one another and draw some observations based on them

R Environment Setup

The following packages are required prior to running this project in your Rstudio environment, by running installed.packages() at your R console, you can confirm your list of packages.*

To install the following packages, simply run install.packages('pachage-name')

- List of Packages
- car - Companion to Applied Regression
- Hmisc - Harrell Miscellaneous
- tinytex - To build pdf renders using knit
- tidyverse - To perform more advanced data transformations
- corrr - Performing Correlation in R
- knitr - For R markdown tables, graphs and rendering features.
- ggplot2 - For advanced features for descriptive graphs (line, box, dot,etc)

All packages are documented Here :

The Dataset (Summary View)

This section describes the dataset, variable types, number of observations, schema, dimensions. We also delve into data quality, issues, handling of issues we found. Finally we address data processing and preparation.

```r
# Load the data
load("Corrupt.Rdata")
df_un = data.frame(FMcorrupt)

# Convert to tidyverse object, tibble for additional sql style functionality
tb_un = dplyr::as_tibble(df_un)
```

Dataset size, shape, data gaps, schema and features

- Dataset has 364 rows and 28 columns.
- Shape dimensions are (364, 28).
- Data gaps : blanks(Na represents a blank) ranging from 33 to 180.
- Schema and features:

```r
# Show to dimensions ( rows x columns ) of dataset
dim(tb_un)
```

```
## [1] 364  28
```

```r
# Show summary statistics of all fields(variables) in table
str(tb_un)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    364 obs. of  28 variables:
##  $ wbcode       : chr  "AFG" "AGO" "AGO" "ALB" ...
##  $ prepost      : chr  "" "pre" "pos" "pre" ...
##  $ violations   : num  NA 744.38 15.37 256.63 5.56 ...
##  $ fines        : num  NA 40294 1208 13970 610 ...
##  $ mission      : int  NA 1 1 1 1 1 1 1 1 1 ...
##  $ staff        : int  NA 9 9 3 3 3 3 19 19 4 ...
##  $ spouse       : int  NA 4 4 3 3 2 2 10 10 1 ...
##  $ gov_wage_gdp  : num  NA 1.3 1.3 1.3 1.3 ...
##  $ pctmuslim    : num  NA 0.01 0.01 0.7 0.7 ...
##  $ majoritymuslim: int  NA 0 0 1 1 1 1 0 0 -1 ...
##  $ trade        : num  NA 2.61e+09 2.61e+09 2.72e+07 2.72e+07 ...
##  $ cars_total   : int  NA 24 24 4 4 13 13 15 15 3 ...
##  $ cars_personal : int  NA 3 3 0 0 6 6 14 14 1 ...
##  $ cars_mission  : int  NA 21 21 4 4 7 7 1 1 2 ...
##  $ pop1998      : num  NA 11739390 11739390 3101330 3101330 ...
##  $ gdppcus1998   : num  NA 731 731 1008 1008 ...
##  $ ecaid        : num  NA 92.3 92.3 62.8 62.8 ...
##  $ milaid       : num  NA 0 0 2.2 2.2 ...
##  $ region       : int  NA 6 6 3 3 7 7 2 2 4 ...
##  $ corruption   : num  NA 1.048 1.048 0.921 0.921 ...
##  $ totaid       : num  NA 92.3 92.3 65 65 ...
##  $ r_africa     : int  NA 1 1 0 0 0 0 0 0 0 ...
##  $ r_middleeast  : int  NA 0 0 0 0 1 1 0 0 0 ...
##  $ r_europe     : int  NA 0 0 1 1 0 0 0 0 0 ...
```

```
##  $ r_southamerica: int  NA 0 0 0 0 0 0 1 1 0 ...
##  $ r_asia        : int  NA 0 0 0 0 0 0 0 0 1 ...
##  $ country       : chr  "AFGANISTAN" "ANGOLA" "ANGOLA" "ALBANIA" ...
##  $ distUNplz     : num  0.445 1.554 1.554 1.775 1.775 ...
```

The data table is composed of the following variables (variables are fields):

- Volume of parking violations : Maximum number at 3393, average of 100.
- Total number of diplomats(from each country) : MAximum 86, average of 11.
- Individual country corruption index : -2.5 to a maximum of 1.5
- Fines computed in USD: Maximum of 186163, average of 5579 USD.
- Government wages index : 180 NA records, over 35% of dataset is blank, we have to drop this field from analysis.
- Trade with the US:
- Breakdown of Vehicles : official, personal and total
- Population of Country (as of 1998)
- GDP of country (as of 1998)
- Aid to country : military, economic and total US aid
- Country corruption index
- Continent identification : five variables marking each countries geographical location
- Name of the country and country code
- Proportion of Muslim population

Data quality issues

This section shows the quality of the records, issues we found and steps we took to prepare it for exploratory data analysis.

Table 1: Rows with blank columns values

wbcode	prepost	corruption	violations	gdppcus1998	totaid	gov_wage_gdp	cars_personal	cars_mission	car
AFG		NA	NA	NA	NA	NA	NA	NA	
ARE	pre	-0.7794677	0.00000	21143.5391	NA	NA	6	7	
ARE	pos	-0.7794677	0.00000	21143.5391	NA	NA	6	7	
ATG		NA	NA	NA	NA	NA	NA	NA	
BEN	pre	0.7555962	403.28247	344.9218	21.1	NA	5	3	
BEN	pos	0.7555962	52.00269	344.9218	21.1	NA	5	3	

The above table shows us top 10 rows of 190, where columns are blank. However we notice that we can still filter some of these out by vertical slicing.

Table 2: Rows with blank pre/post tagging

wbcode	prepost	violations	fines	mission	staff	spouse
AFG		NA	NA	NA	NA	NA
ATG		NA	NA	NA	NA	NA
BLZ		NA	NA	NA	NA	NA
BRB		NA	NA	NA	NA	NA
BRN		NA	NA	NA	NA	NA
CPV		NA	NA	NA	NA	NA

Table 3: Rows with blank violations

wbcode	prepost	violations	fines	mission	staff	spouse
AFG		NA	NA	NA	NA	NA
ATG		NA	NA	NA	NA	NA
BLZ		NA	NA	NA	NA	NA
BRB		NA	NA	NA	NA	NA
BRN		NA	NA	NA	NA	NA
CPV		NA	NA	NA	NA	NA

Table 4: Rows with blank columns values post processing

wbcode	prepost	corruption	violations	gdppcus1998	totaid
ARE	pre	-0.7794677	0.0000000	21143.54	NA
ARE	pos	-0.7794677	0.0000000	21143.54	NA
BIH	pre	0.3488850	209.6420593	1075.86	149.4
BIH	pos	0.3488850	0.6541219	1075.86	149.4
CHE	pre	-2.5829878	0.8102109	32975.70	0.0
CHE	pos	-2.5829878	0.0000000	32975.70	0.0

The above tables shows us a total of 10 rows with scattered NA values which we can still utilize as the main variables we are interested in are still intact.

~~There are 66 rows that have empty string for prepost and the associated data for the other columns for these rows are 'NA' , the only column that has value for these are 'wbcode'. It is possible that the data is not either observerd or entered into the data set. These rows do not provide any meaningful information and do not add any additional value to the analysis and it can be safely removed.~~

Summary of data processing and preparation

We performed the following modifications to make the data more uniform. Here are the changes,

1. Removed the 62 rows above where prepost is blank.

2. Removed the 4 rows where violations are blank, without this data, the record is not useful for our analysis.

3. Calculate average violations per nation to perform average analysis per diplomat.

4. Calculate revised trade in millions, population in millions as aid is presented in millions, this steps makes the unit for these to be the same.

5. Vertical slicing of cars data and diplomat wage index due to excessive blanks.

Table 5: Sample of revised fields

country	corruption	avg_viols	totaid	ecaid	trade_mil	pop_mil	gdp_1000s
ANGOLA	1.05	83	92.3	92.3	2606	12	0.73
ANGOLA	1.05	2	92.3	92.3	2606	12	0.73
ALBANIA	0.92	86	65.0	62.8	27	3	1.01
ALBANIA	0.92	2	65.0	62.8	27	3	1.01
	-0.78	0	NA	NA	3030	3	21.14
	-0.78	0	NA	NA	3030	3	21.14

Table 6: Rows with NA values

country	corruption	avg_viols	totaid	ecaid	trade_mil	pop_mil	gdp_1000s
	-0.78	0	NA	NA	3030	3	21.14
	-0.78	0	NA	NA	3030	3	21.14
BOSNIA-HERZEGOVINA	0.35	35	149.4	97.5	NA	4	1.08
BOSNIA-HERZEGOVINA	0.35	0	149.4	97.5	NA	4	1.08
MONTENEGRO & SERBIA	0.97	39	NA	NA	47	11	0.94
MONTENEGRO & SERBIA	0.97	0	NA	NA	47	11	0.94
ZAIRE	1.58	6	22.4	22.4	NA	48	0.10
ZAIRE	1.58	0	22.4	22.4	NA	48	0.10

Univariate Analysis for key variables

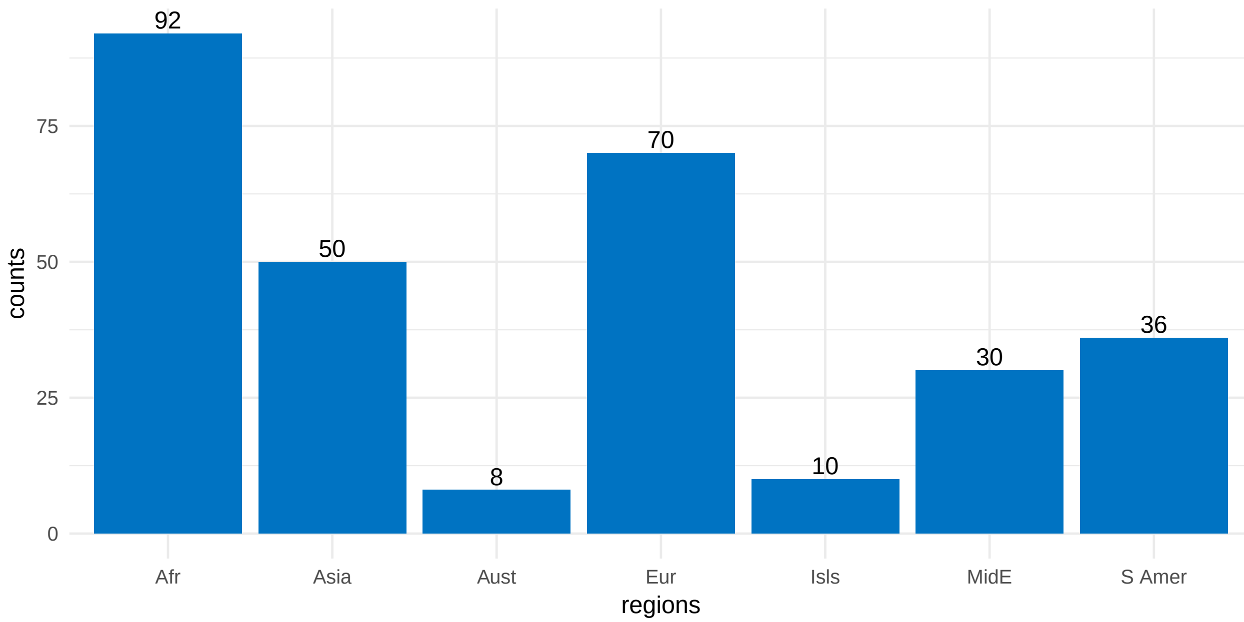
Here we review at a glance some key descriptive features of all the variables we have been provided.

1. Country and Country code. Here we also talk about the regions and boolean flags for each major region. Our goal is to view the depth of the dataset here. Hence we compute a grouped view of countries by region.

At a glance we observe the regions as following:

1 Caribbean Islands 2 south_americas 3 Europe 4 asia 5 Australia 6 Africa 7 middle east

Each of these continents have a boolean variable : Africa, Middle East, South America, Asia.



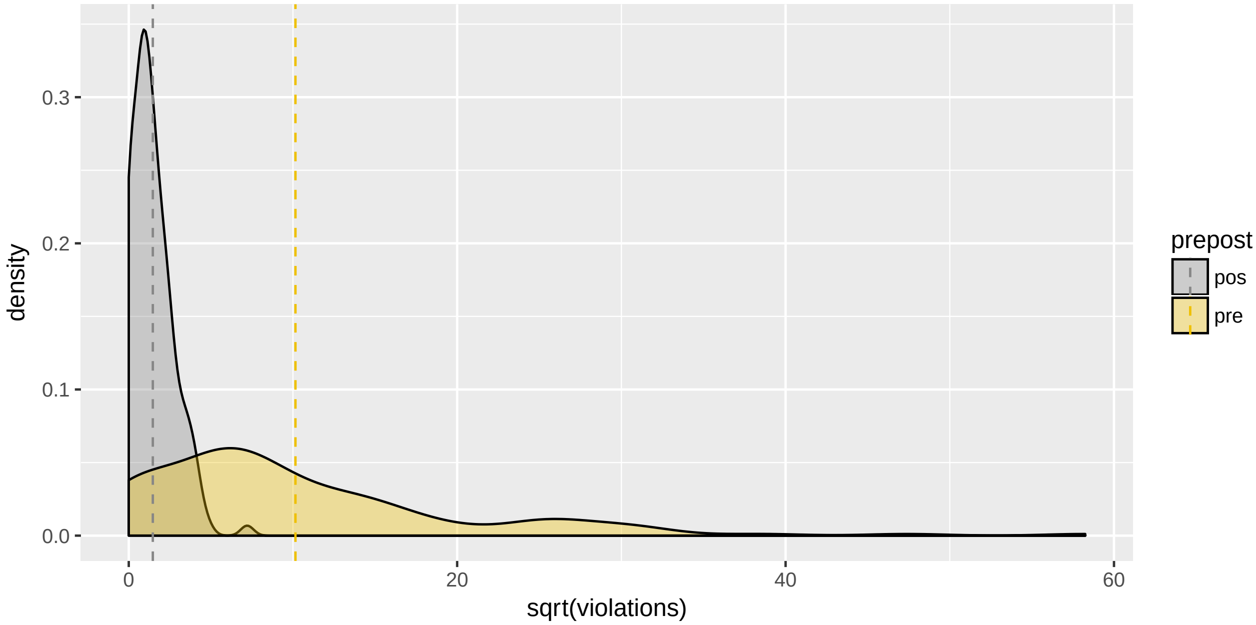
This is a text field where we found a total of 364 rows. There are 60 rows with no values.

- Pre and Post 2002 records

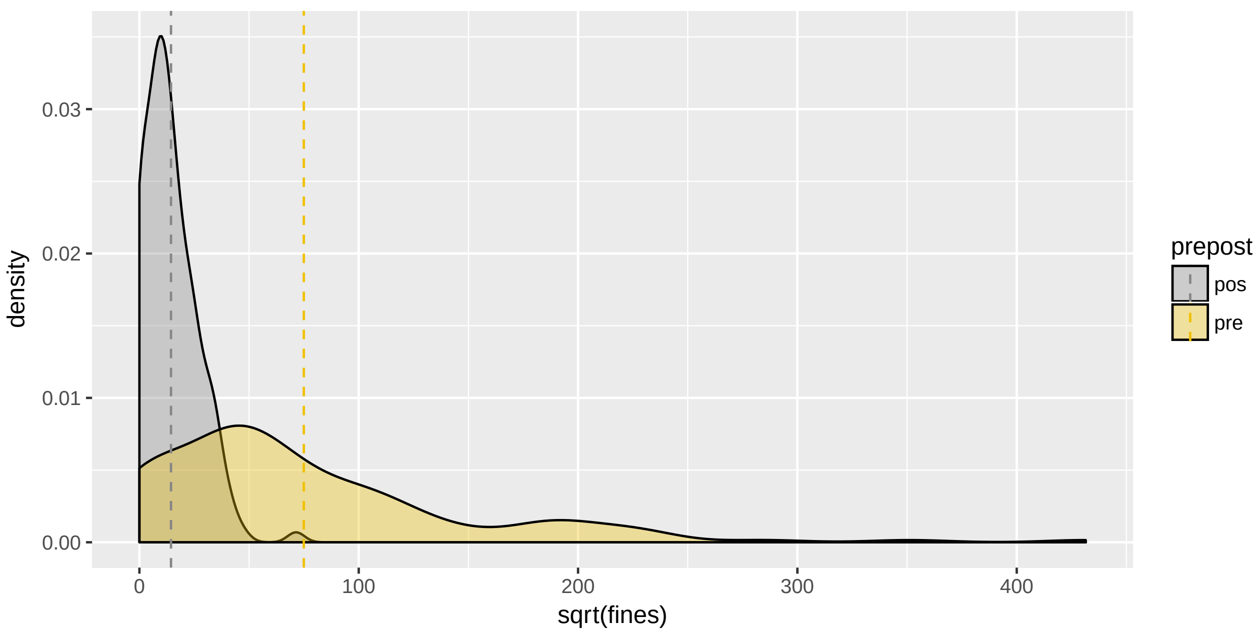
This field tags the row for a pre or post parking enforcement summary of violations.

- Volume of parking violations :

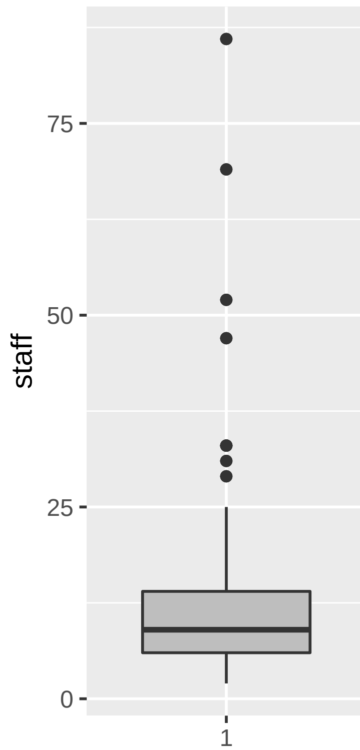
(a) Before enforcement : Very high mean, max, a lot of overall violations, however, post enforcement the distribution has a much smaller magnitude. We took a square root of the violations as there are a few very large values that make the graph very hard to review. We clearly see a major decline in the pre vs post number of violations. Also the mean is noteworthy.

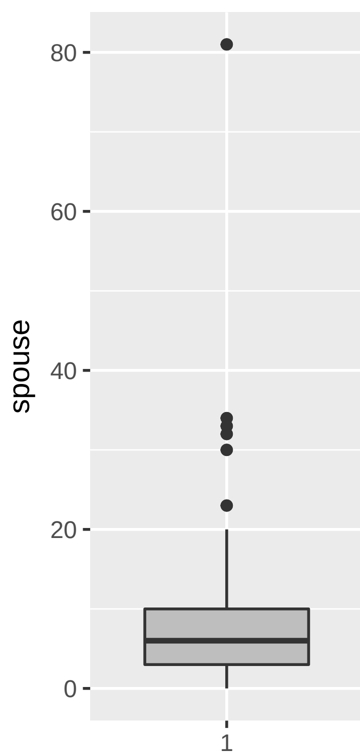


- Fines computed in USD: As fines are dependend on the number of violations, we see similar decline in distribution of fines owed after the enforcement. As fines have a very skewed distribution, visually the histogram is hard to review, hence we computer a square root to see the distribution better. We see see that missions have been fined a lot more before enforcement of fines however after the enforcement the missions have dramatically reduced fines owed.



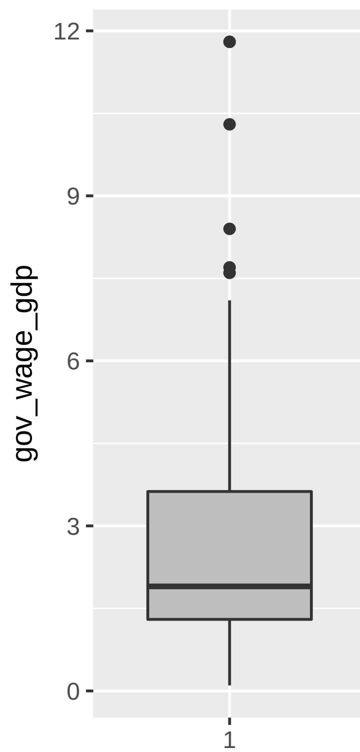
- Diplomatic mission details
- Total number of diplomats(from each country) - Majority of missions have under 20 diplomats.
- total number of family members - Most missions have under 20 family members.





- Government wages index : Here we notice a most diplomats getting paid within 2-4 times the GDP of their country. We have to keep in mind that this index by itself is not helpful as GDP varis a lot by country. Also we decided to remove this field from our analysis as this has over 180 NA values. *We notice that government diplomat compensation varies a lot, from 10% to over 1100% of the GDP. The mean is 280%. Not all nations have a similar cost of living as does the US, so this major disparity between GDP and government diplomat wages is noteworthy. We will further evaluate this in this* *project.* Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.100 1.300 1.900 2.828 3.625 11.800 180

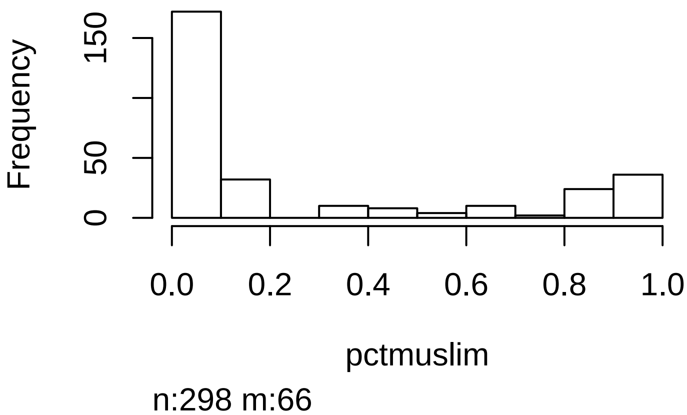
```
## Warning: Removed 180 rows containing non-finite values (stat_boxplot).
```



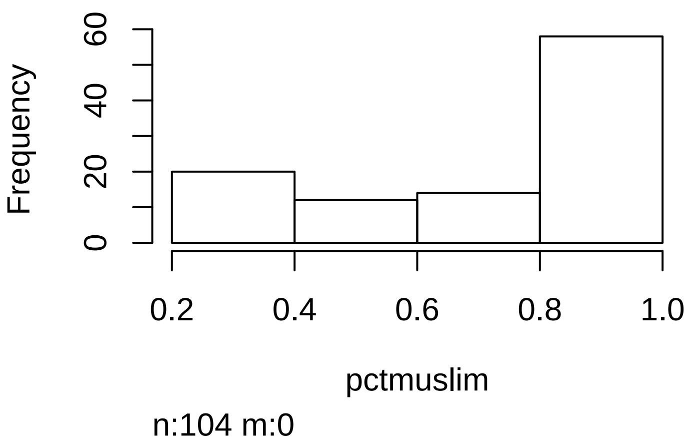
- Individual country corruption index : -2.5 to a maximum of 1.5. We know this is a composite index where a higher number means more corruption.

- Proportion of Muslim population
- Percentage of Muslim population - We see in the 2 histograms the distribution. The first has all nations where we see over 150 nations with a 0. Hence we build a second histogram with at least 20% population muslim. This view shows us the distribution of over 75 nations with at least 60% muslim population.
- Majority Muslim population - this is a boolean 0 or 1 flag to indicate majority are muslim.

```
hist(select(tb_un,pctmuslim), breaks = 0:1 - .01, main = "Percentage of Muslim Population",
     xlab = NULL)
```




```
hist(select(filter(tb_un,pctmuslim > 0.2),pctmuslim), breaks = 0:1 - .01, main = "At least 20% of popul
     xlab = NULL)
```



- Trade with the US: the trade relationships have a massive range from less than 100000 to several billions.

  Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.000e+00 8.911e+07 5.194e+08 1.025e+10 4.796e+09 3.290e+11 4

- Breakdown of Vehicles : official, personal and total

- Total number of cars

- Breakdown of person and official cars

[1] "Personal cars" Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.000 1.000 2.000 5.324 6.000 64.000 86 [1] "Mission cars" Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.000 2.000 3.000 5.144 6.000 116.000 86 [1] "Total cars" Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 1.00 3.00 7.00 10.47 12.00 116.00 86 * Population of Country (as of 1998) : We find a large range here from population into just under half a million to over billion people.

```
 Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
```

5.308e+05 3.815e+06 8.852e+06 3.655e+07 2.341e+07 1.242e+09

- GDP of country (as of 1998) : We notice here extremely poor nations with the lowest GDP as 95, a mean of about 5000 and as high as 36485. *We notice here too a huge disparity between nations. At the lowest end we see a GDP of only 95, average of 5236 and maximum of 36485. To equalize this a bit, we will compute a total compensation using the wage index by multiplying wage index to gdp, which together will give us a sense of total compensation. This allows us to use the variable better as the index while very useful does not help us understand the poverty or wealth of nations and their diplomats income.* Min. 1st Qu. Median Mean 3rd Qu. Max. 95.45 412.07 1374.88 5044.09 4936.62 36485.64

Table 7: Lowest GDP

gdppcus1998	country
95.44793	ETHIOPIA
95.44793	ETHIOPIA
101.49330	ZAIRE
101.49330	ZAIRE
105.59200	BURUNDI
105.59200	BURUNDI
123.56780	LIBERIA
123.56780	LIBERIA
137.54359	SIERRA LEONE
137.54359	SIERRA LEONE

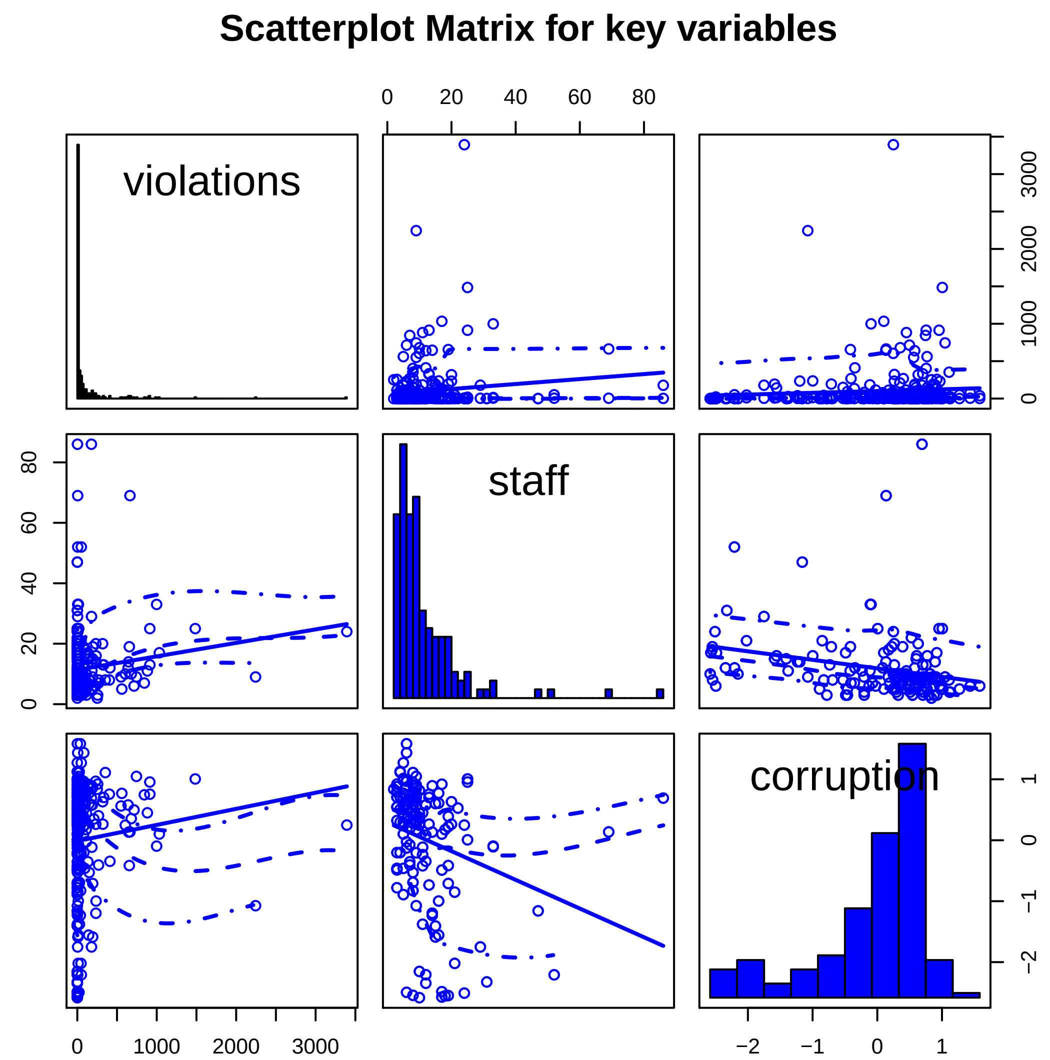
Table 8: Highest GDP

gdppcus1998	country
36485.64	JAPAN
36485.64	JAPAN
35855.47	
35855.47	
32975.70	SWITZERLAND
32975.70	SWITZERLAND
28281.00	DENMARK
28281.00	DENMARK
24806.11	
24806.11	
Aid to count	ry :
+ military :	We notice that aid to have a massive range, while the mean is relatively small at 0.2 million, we find nation
+ economic :	Here we see the mean at 49 million and about 75% of aid below 40 million. There are some nations reseivin
+ total US a	id : Here we find 75% of all aid below 42 million with the highest aid to Israel, Egypt and Colombo.

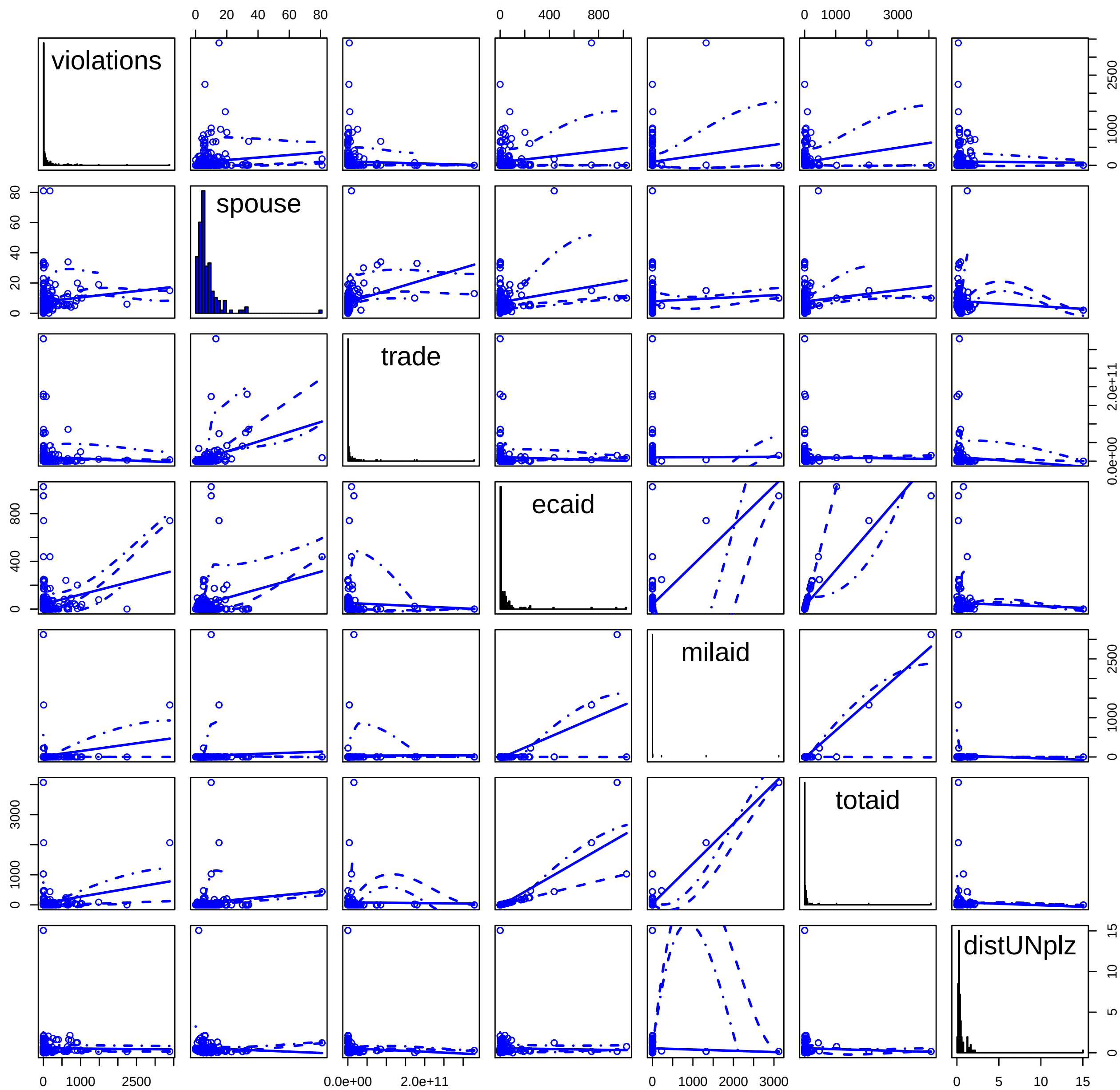
[1] "Economic aid" Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.00 0.00 8.70 49.27 40.30 1026.10 4 [1] "Military aid" Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.000 0.000 0.200 33.048 0.775 3120.000 4 [1] "Total aid" Min. 1st Qu. Median Mean 3rd Qu. Max. NA's 0.000 0.325 9.000 82.320 42.950 4069.100 4 *Index variable for 'distUNplz' - Insufficiant information about this column.

This section needs clarification, modification of variables to improve relationships ## Analysis of key relationships

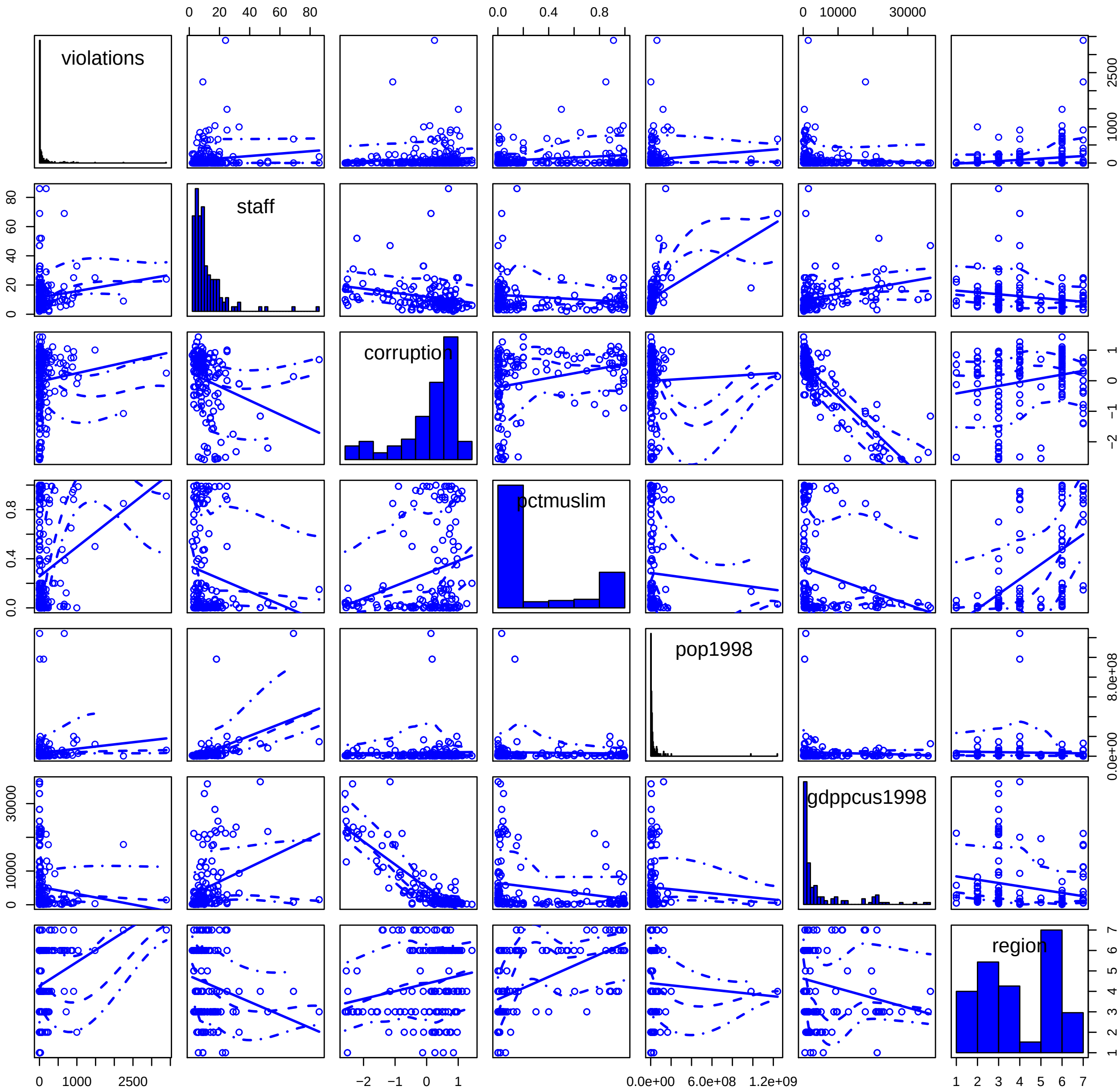
Our first step is preliminary check across all key variables such as violations, staff and corruption. Interestingly, we found that there is no immediate evidence that the more the number of diplomats, the higher the violations. Most of the violations appears clustered at the lower bounds of the staff number between 0 and 20. However we observed an interesting pattern between violations and corruption. The more corrupt the country is, i.e., indicated by the corruption index, the more likely we would see the violation events.



Scatterplot Matrix for key variables



Scatterplot Matrix for key variables



Specific questions we have identified for exploration: ** Need to filter responses and fill this one**

(a) Was there a relationship between corruption and parking violations?

(b) How does the number of diplomats contribute to the frequency of violations?

(c) Does the legislative change in October 2002 dramatically change volume of violations?

(d) Does the ranking of corruption index (descending order) show a relationship to the volume of parking violations(per diplomat)?

(e) Does the level of aid to the country or trade with country show relationship to the volume of parking violations(per diplomat)

(f) Does the country gdp, diplomat wage have a relationship to corruption index? i.e. what could have a statistical correlation to a culture of engaging in negligent acts of corruption.

(g) Does WTC attack impact on parking violations?

(h) Which country have the largest diplomatic footprint, including family and is there a relationship with violations ?

(i) What is the ralationship between GDP and diplomatic wage ?

(j) What is the relationship between economic aid, military aid and other country data like population, GDP?

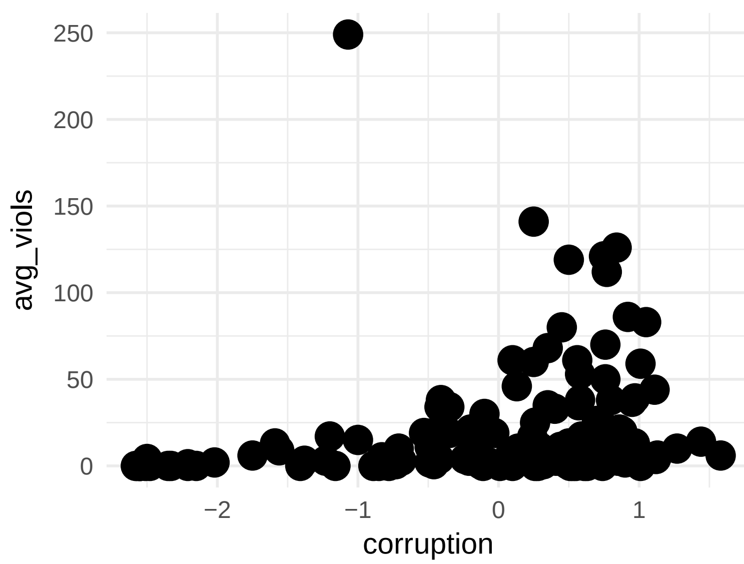
(j) Which country have more cars? If so, more cars means more staff?

correlation between 'cars_total' and question 2 answer. Those are a few questions I haven't answered yet. I think we can work on those questions with our own variables assignments. When you assign the new variable, comments with a bit more description so that in final RMD, I can go through all the variables and change them all to make it consistent.

This correlation and graphs need review and modification

Table 9: Correlation - Pre 2002

rowname	corruption	totaid	avg_viols	trade_mil	gdp_1000s
corruption	NA	-0.0407963	0.1830667	-0.3382683	-0.8619694
totaid	-0.0407963	NA	0.0855975	-0.0119217	0.0486442
avg_viols	0.1830667	0.0855975	NA	-0.1196477	-0.1518583
trade_mil	-0.3382683	-0.0119217	-0.1196477	NA	0.4111201
gdp_1000s	-0.8619694	0.0486442	-0.1518583	0.4111201	NA

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## Warning: Removed 2 rows containing missing values (geom_point).
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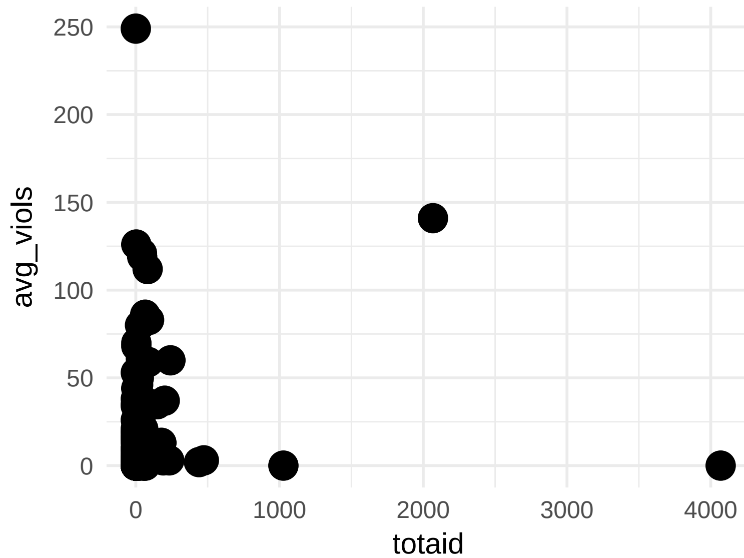


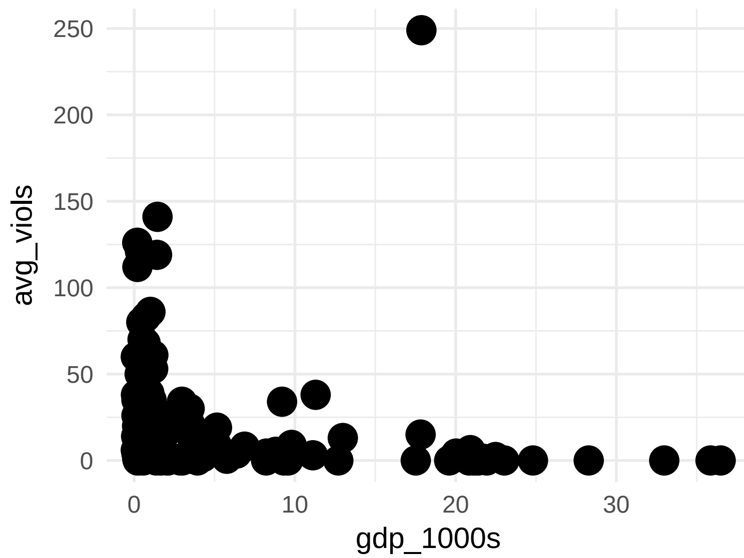
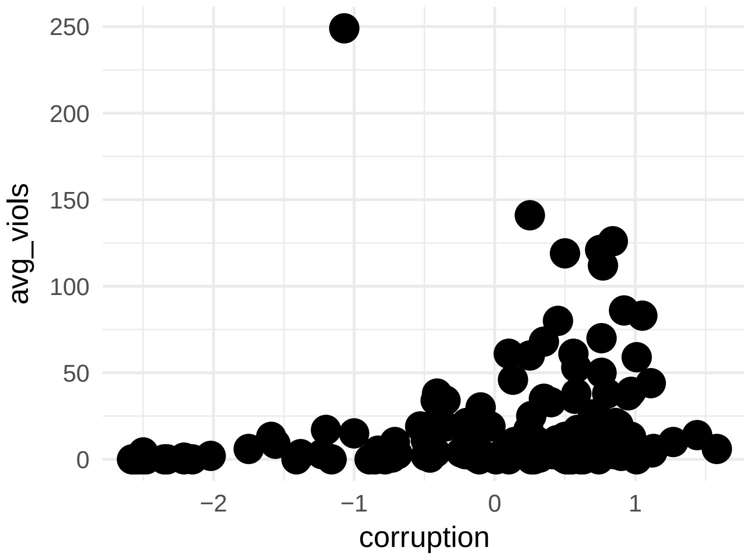


Table 10: Correlation - Post 2002

rowname	corruption	totaid	ecaid	milaid	avg_viols	trade_mil	pop_mil	gdp_1000s
corruption	NA	-0.0407963	0.0875437	-0.0996862	0.2110147	-0.3382683	0.0270581	-0.8619694
totaid	-0.0407963	NA	0.8429109	0.9638705	-0.0543492	-0.0119217	0.0154283	0.0486442
ecaid	0.0875437	0.8429109	NA	0.6691352	-0.0544377	-0.0393562	0.0704715	-0.0726040
milaid	-0.0996862	0.9638705	0.6691352	NA	-0.0481151	0.0030107	-0.0135790	0.1031294
avg_viols	0.2110147	-0.0543492	-0.0544377	-0.0481151	NA	-0.0929531	-0.0005111	-0.1534943
trade_mil	-0.3382683	-0.0119217	-0.0393562	0.0030107	-0.0929531	NA	0.2116664	0.4111201
pop_mil	0.0270581	0.0154283	0.0704715	-0.0135790	-0.0005111	0.2116664	NA	-0.0500077
gdp_1000s	-0.8619694	0.0486442	-0.0726040	0.1031294	-0.1534943	0.4111201	-0.0500077	NA
NA	NA	NA	NA	NA	NA	NA	NA	NA
NA	NA	NA	NA	NA	NA	NA	NA	NA

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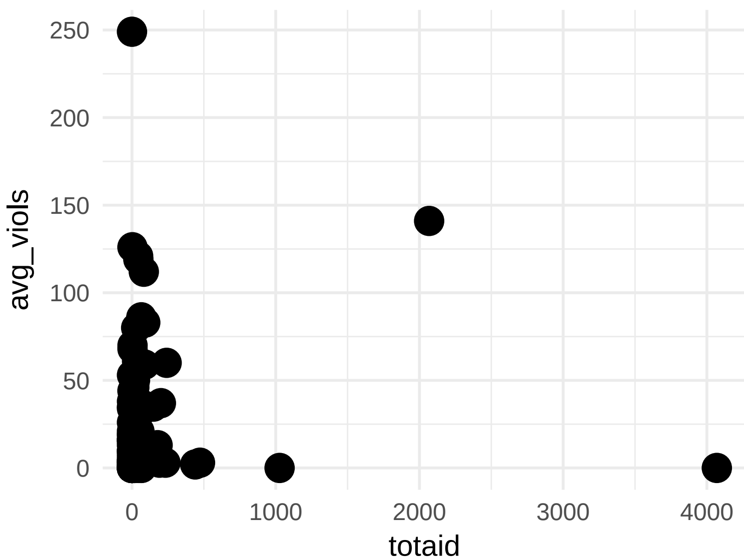
## Warning: Removed 2 rows containing missing values (geom_point).
```



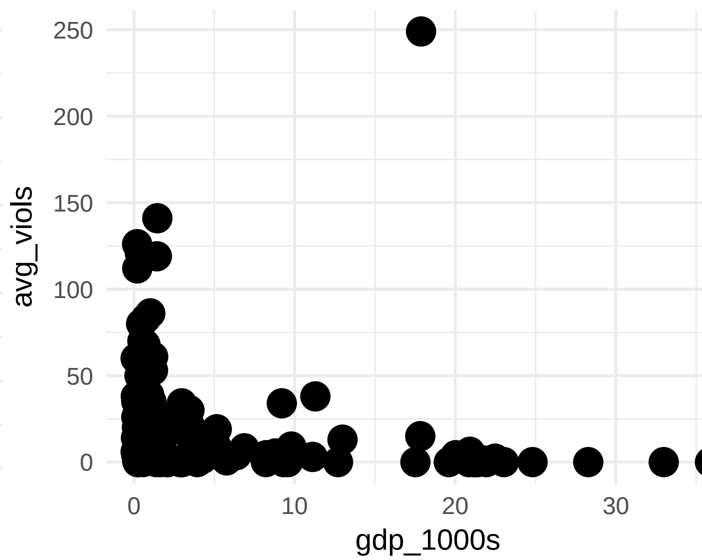


Table 11: Parking Violation side by side (pre / post enforcement)

country	pre_2002_violations	pos_2002_violations
KUWAIT	249	0
EGYPT	141	0
CHAD	126	0
SUDAN	121	0
BULGARIA	119	2
MOZAMBIQUE	112	0
ALBANIA	86	2
ANGOLA	83	2
SENEGAL	80	0
PAKISTAN	70	1
IVORY COAST	68	0
MOROCCO	61	0
ZAMBIA	61	0

country	pre_2002_violations	pos_2002_violations
ETHIOPIA	60	1
NIGERIA	59	0
SYRIA	53	1
BENIN	50	7
ZIMBABWE	46	1
CAMEROON	44	3
MONTENEGRO & SERBIA	39	0
BAHRAIN	38	1
BURUNDI	38	0
MALI	38	1
INDONESIA	37	1
BOSNIA-HERZEGOVINA	35	0

DUPLICATE - CAN WE REMOVE THESE?

We looked at the total number of violations and found that the violations could be as low as 0 and could also go as frequent as 3392.96. This shows a wide discrepancy in violations, from which we could gather some insightful information regarding other factors such as corruption index and the number of diplomats visits to the US.

Looking at the diplomat variable, i.e., staff, we notice that diplomat numbers stay between 0 and 86~~

~~The column'prepost' plays a key role in the defintion of the dataset and identifies whether the data is prior or post to the parking enforcement implemented in 2002. This dataset appears to be in the form of Panel or Longitudinal Data. It has both cross-sectional (Data around corruptions , violations etc) and a time series (pre vs post) dimension.

1. violations

```
summary(FMcorrupt$violations)
```

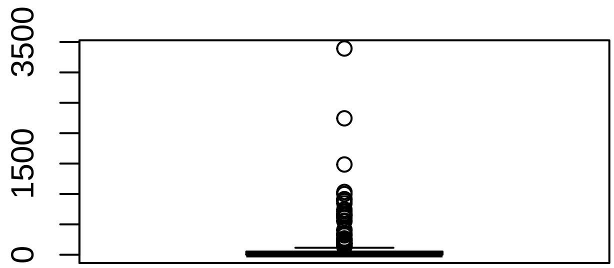
```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's
##    0.000    0.654    5.724  100.879   51.915 3392.961       66
```

```
Hmisc::describe(FMcorrupt$violations)
```

```
## FMcorrupt$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      298       66      159    0.995    100.9    171.8   0.0000   0.0000
##      .25      .50      .75      .90      .95
##   0.6541   5.7236  51.9148 234.7586 640.8059
##
## lowest :    0.0000000    0.3270609    0.4051054    0.6076581    0.6541219
## highest:  998.5848999 1033.0189209 1484.9139404 2244.2841797 3392.9606934
```

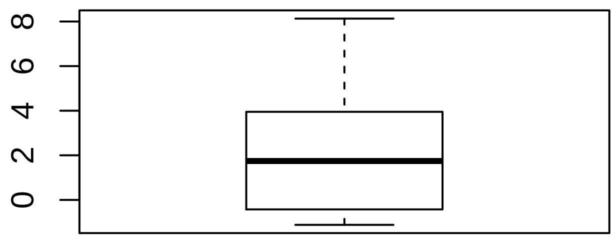
It appears that 3/4th of dataset habe the violations that is less than 51.9 and where as 95% of the rows have value less than or equal to 640.8 with the maximum value being 3392.9. The distribution seems to be skewed to the right. Let us do the boxplot and see the outliers clearly.

```
boxplot(FMcorrupt$violations)
```



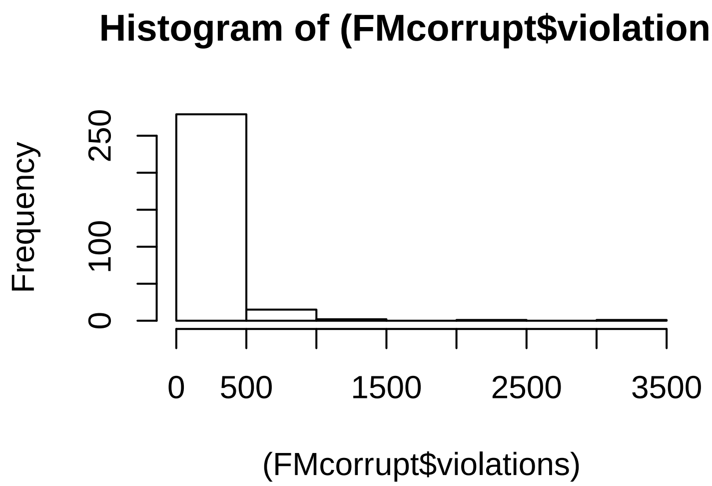

```r
boxplot(log(FMcorrupt$violations))
```

```
## Warning in bplt(at[i], wid = width[i], stats = z$stats[, i], out =
## z$out[z$group == : Outlier (-Inf) in boxplot 1 is not drawn
```

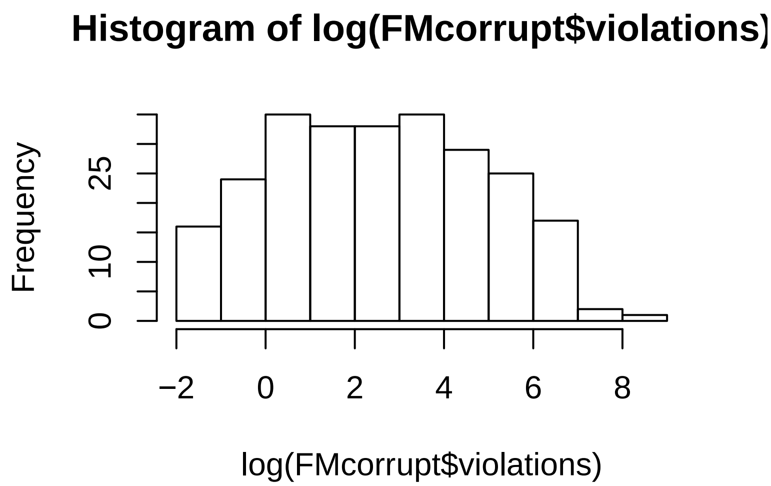


It is very clear from the boxplot that majority of the values are below the value 51.9 , transforming the violations to the log scale gives a better picture.

```r
hist((FMcorrupt$violations))
```




```r
hist(log(FMcorrupt$violations))
```



2. prepost

```
pre <- FMcorrupt[FMcorrupt$prepost =='pre',]
pos <- FMcorrupt[FMcorrupt$prepost =='pos',]
```

Let's divide the data into two set and analyse the key variable 'violations'

```
Hmisc::describe(pre$violations)
```

```
## pre$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      149        2      123    0.998    198.1    290.3     0.00     0.00
##      .25      .50      .75      .90      .95
##    17.22    51.65   189.59   641.12   867.01
##
## lowest :    0.0000000    0.4051054    0.6076581    0.8102109    1.0127636
## highest:  998.5848999 1033.0189209 1484.9139404 2244.2841797 3392.9606934
```

```
Hmisc::describe(pos$violations)
```

```
## pos$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      149        2       37     0.99    3.688    4.925   0.0000   0.0000
##      .25      .50      .75      .90      .95
##   0.3271   1.3082   4.5789  10.0081  14.5869
##
## lowest :  0.0000000  0.3270609  0.6541219  0.9811828  1.3082438
## highest: 16.3530464 17.6612911 18.3154125 22.8942661 52.0026894
```

It is very interesting to the see mean value drop from 198.1 to 3.688 indicating such a huge change in the behaviour of diplomats since the enforcement of legal penalties and removing the immunity.

END OF ————————————————- DUPLICATE

Analysis of Key Relationships

(a) Was there a relationship between corruption and parking violations?

** Suggest using the tibble tables which allow more filtering options**

Our first step is to subset the corruption index data to further zoom in to the most corrupted countries. We created subcases with below and above zero.

```
subcases_above_zero = 0 <= FMcorrupt$corruption & !is.na(FMcorrupt$corruption)
```

```
subcases_below_zero = 0 >= FMcorrupt$corruption & !is.na(FMcorrupt$corruption)
```

```
FM_subcases_above_zero = FMcorrupt[subcases_above_zero, ]
nrow(FM_subcases_above_zero)
```

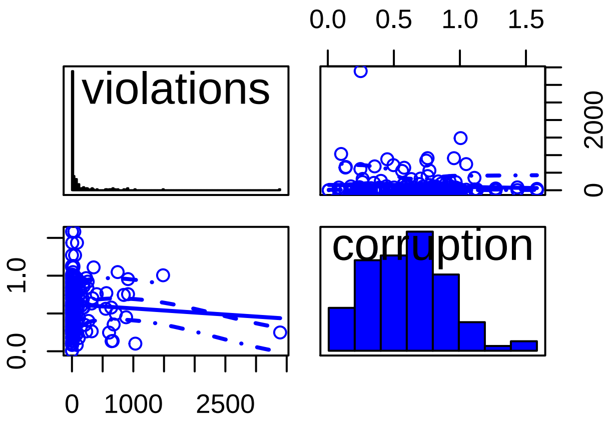
```
## [1] 196
```

```
FM_subcases_below_zero = FMcorrupt[subcases_below_zero, ]
nrow(FM_subcases_below_zero)
```

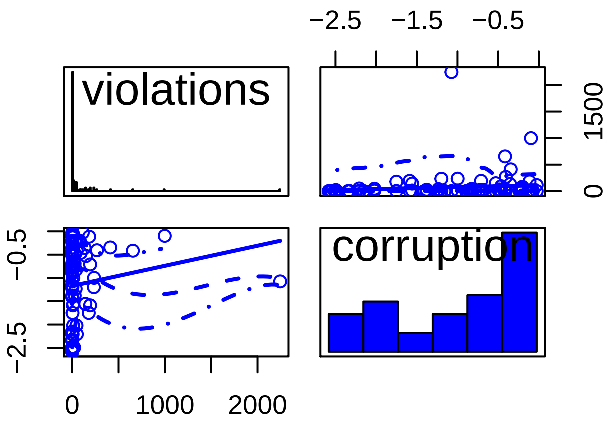
```
## [1] 107
```

We also removed any corruption observations where the event is "NA". Using the logical vector to pull out from the original data, we found that the total number of observation above corruption index 0 is 196 and observation below corruption index 0 is 107 .

```
car::scatterplotMatrix(~ violations + corruption, data=FM_subcases_above_zero, diagonal=list(method="his
```




```
car::scatterplotMatrix(~ violations + corruption, data=FM_subcases_below_zero, diagonal=list(method="his
```




```
cor(FMcorrupt$corruption, FMcorrupt$violations, use="complete.obs")
```

```
## [1] 0.07884143
```

```
cor_below = cor(FM_subcases_below_zero$corruption, FM_subcases_below_zero$violations, use ='complete.obs
cor_below
```

```
## [1] 0.1242881
```

```
cor_above = cor(FM_subcases_above_zero$corruption, FM_subcases_above_zero$violations, use ='complete.obs
cor_above
```

```
## [1] -0.05543683
```

(b) Does religion have a role in the behaviour and violations

```
#car::scatterplot( log(violations) ~ pctmuslim       , data=FMcorrupt,
 #  ylab="Corruption", xlab="% Muslim",
  # main="Enhanced Scatter Plot"
 #  )

cor(FMcorrupt$violations,FMcorrupt$pctmuslim,use="complete.obs")
```

```
## [1] 0.1968958
```

This plot shows that there is not much relationship between the religion and the behaviour (violations) , there are too many observations with the % muslim close to 0 and as well as 1. So the violations cannot be directly related %muslim.

(b) Does number of cars have a role in the behaviour and violations

```
#car::scatterplot( log(violations) ~ cars_total       , data=FMcorrupt,
#   ylab="Corruption", xlab="# of Cars",
#   main="Enhanced Scatter Plot"
 #  )

cor(FMcorrupt$violations,FMcorrupt$cars_total,use="complete.obs")
```

```
## [1] 0.1614551
```

Behaviour based on the continets

** regional behavior can be plotted much more easily as following , can we remove this section?**

```
africa <- FMcorrupt[FMcorrupt$r_africa ==1 & !is.na(FMcorrupt$r_africa),]
nrow(africa)/2
```

```
## [1] 46
```

```
asia <- FMcorrupt[FMcorrupt$r_asia ==1 & !is.na(FMcorrupt$r_asia),]
nrow(asia)/2
```

```
## [1] 26
```

```
europe <- FMcorrupt[FMcorrupt$r_europe ==1 & !is.na(FMcorrupt$r_europe),]
nrow(europe)/2
```

```
## [1] 35
```

```
southamerica <- FMcorrupt[FMcorrupt$r_southamerica ==1 & !is.na(FMcorrupt$r_southamerica),]
nrow(southamerica)/2
```

```
## [1] 18
```

```r
middleeast <- FMcorrupt[FMcorrupt$r_middleeast ==1 & !is.na(FMcorrupt$r_middleeast),]
nrow(middleeast)/2
```

```
## [1] 15
```

```r
Hmisc::describe(africa$violations)
```

```
## africa$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##       92        0       72    0.999    136.6    216.2   0.0000   0.3271
##      .25      .50      .75      .90      .95
##   2.3953  15.5354 110.4419 559.6532 708.7320
##
## lowest :    0.0000000    0.3270609    0.6541219    0.9811828    1.3082438
## highest:  744.3812256  844.0371704  882.3196411 1033.0189209 1484.9139404
```

```r
Hmisc::describe(asia$violations)
```

```
## asia$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##       50        2       39    0.998     73.1    118.6   0.0000   0.2944
##      .25      .50      .75      .90      .95
##   0.7359  11.2836  54.5373 196.3141 297.4689
##
## lowest :   0.0000000   0.3270609   0.6541219   0.9811828   1.3082438
## highest: 233.1381836 267.1670227 322.2613831 663.1575928 913.1076660
```

```r
Hmisc::describe(europe$violations)
```

```
## europe$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##       70        0       46    0.991    46.49    76.03   0.0000   0.0000
##      .25      .50      .75      .90      .95
##   0.3466   2.9519  34.7378 179.2389 221.4509
##
## lowest :   0.0000000   0.3270609   0.4051054   0.6541219   0.8102109
## highest: 209.6420593 231.1126556 236.1764679 256.6343079 714.2008667
```

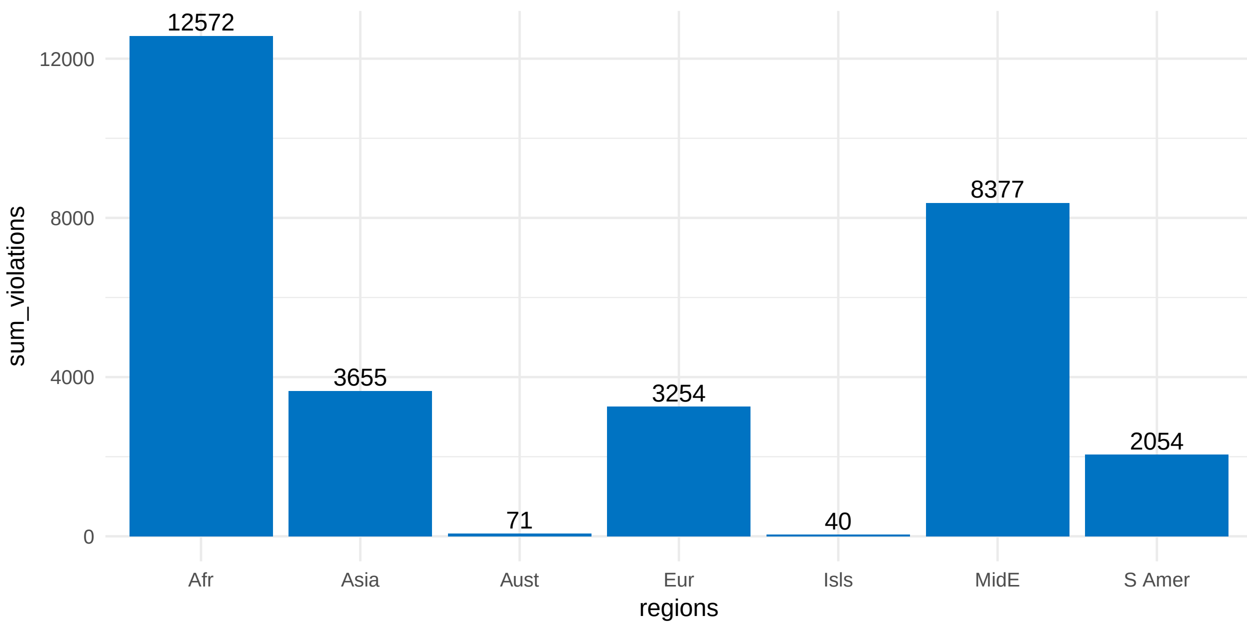
```r
Hmisc::describe(southamerica$violations)
```

```
## southamerica$violations
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##       36        0       26    0.989    57.05    98.85   0.0000   0.0000
##      .25      .50      .75      .90      .95
##   0.5724   3.2706  35.8518 113.0244 204.0719
##
## Value          0     2     4     6     8    12    18    28    34    44
## Frequency     12     5     3     1     1     1     1     2     1     1
## Proportion 0.333 0.139 0.083 0.028 0.028 0.028 0.028 0.056 0.028 0.028
##
## Value         50    76    78   148   194   234   998
## Frequency      1     2     1     1     1     1     1
## Proportion 0.028 0.056 0.028 0.028 0.028 0.028 0.028
```

```r
Hmisc::describe(middleeast$violations)
```

```
## middleeast$violations
```

```
##          n   missing  distinct      Info      Mean       Gmd       .05
##         30         0        20      0.98     279.2     500.7 0.000e+00
##        .10       .25       .50       .75       .90       .95
## 0.000e+00 8.177e-02 4.315e+00 6.218e+01 6.672e+02 1.646e+03
##
## lowest :    0.0000000    0.3270609    0.6541219    1.3082438    4.0510545
## highest:  410.9794617  639.8640137  913.7153320 2244.2841797 3392.9606934
```



Results – Need to rewrite this section

Upon checking the violations Vs corruption based on corruption index centered at '0', we observed that corruption is relevant in predicting the parking violation when the index is below 0 as indicated by our correlation value at 0 . However observation above the corruption index of "1""", we do not observe a strong relationship between the corruption and the parking violations as indicated by the negative value -0.06 . This somehow indicates that we need to further fine tune our data analysis with more variables in investigation of corruption index and parking violations.

(b) How does the number of diplomats contribute to the frequency of violations?

As we observe that there are countries with the total number of diplomats at NA, we are interested in the average number of parking violations per individual diplomats. In order to do so, we divided the violations variable by the staff number in each country. However as there are some missing value in these two variables, we first created a subdata which do not have a missing value in two critical variables, i.e., violations and staff.

```
subcases_per_dip = ! is.na(FMcorrupt$violations) & ! is.na(FMcorrupt$staff)
FM_subcases_per_dip = FMcorrupt[subcases_per_dip, ]
FM_subcases_per_dip$vpd = (FM_subcases_per_dip$violations/FM_subcases_per_dip$staff)
summary(FM_subcases_per_dip)
```

```
##     wbcode            prepost            violations
##  Length:298         Length:298         Min.   :   0.000
##  Class :character   Class :character   1st Qu.:   0.654
```

```
##  Mode  :character   Mode  :character   Median :   5.724
##                                        Mean   : 100.879
##                                        3rd Qu.:  51.915
##                                        Max.   :3392.961
##
##      fines             mission      staff           spouse
##  Min.   :     0.00   Min.   :1   Min.   : 2.00   Min.   : 0.000
##  1st Qu.:    65.41   1st Qu.:1   1st Qu.: 6.00   1st Qu.: 3.000
##  Median :   579.72   Median :1   Median : 9.00   Median : 6.000
##  Mean   :  5579.60   Mean   :1   Mean   :11.81   Mean   : 7.758
##  3rd Qu.:  2999.05   3rd Qu.:1   3rd Qu.:14.00   3rd Qu.:10.000
##  Max.   :186163.17   Max.   :1   Max.   :86.00   Max.   :81.000
##
##   gov_wage_gdp      pctmuslim        majoritymuslim        trade
##  Min.   : 0.100   Min.   :0.000000   Min.   :-1.0000   Min.   :0.000e+00
##  1st Qu.: 1.300   1st Qu.:0.006375   1st Qu.: 0.0000   1st Qu.:8.911e+07
##  Median : 1.900   Median :0.050000   Median : 0.0000   Median :5.194e+08
##  Mean   : 2.828   Mean   :0.280317   Mean   : 0.2517   Mean   :1.025e+10
##  3rd Qu.: 3.625   3rd Qu.:0.547500   3rd Qu.: 1.0000   3rd Qu.:4.796e+09
##  Max.   :11.800   Max.   :0.999000   Max.   : 1.0000   Max.   :3.290e+11
##  NA's   :114      NA's   :4          NA's   :4         NA's   :4
##    cars_total     cars_personal     cars_mission        pop1998
##  Min.   :  1.00   Min.   : 0.000   Min.   :  0.000   Min.   :5.308e+05
##  1st Qu.:  3.00   1st Qu.: 1.000   1st Qu.:  2.000   1st Qu.:3.815e+06
##  Median :  7.00   Median : 2.000   Median :  3.000   Median :8.852e+06
##  Mean   : 10.47   Mean   : 5.324   Mean   :  5.144   Mean   :3.655e+07
##  3rd Qu.: 12.00   3rd Qu.: 6.000   3rd Qu.:  6.000   3rd Qu.:2.341e+07
##  Max.   :116.00   Max.   :64.000   Max.   :116.000   Max.   :1.242e+09
##  NA's   :20       NA's   :20       NA's   :20
##   gdppcus1998          ecaid             milaid            region
##  Min.   :   95.45   Min.   :   0.00   Min.   :   0.000   Min.   :1.000
##  1st Qu.:  412.07   1st Qu.:   0.00   1st Qu.:   0.000   1st Qu.:3.000
##  Median : 1374.88   Median :   8.70   Median :   0.200   Median :4.000
##  Mean   : 5044.09   Mean   :  49.27   Mean   :  33.048   Mean   :4.372
##  3rd Qu.: 4936.62   3rd Qu.:  40.30   3rd Qu.:   0.775   3rd Qu.:6.000
##  Max.   :36485.64   Max.   :1026.10   Max.   :3120.000   Max.   :7.000
##                     NA's   :4         NA's   :4          NA's   :2
##    corruption           totaid            r_africa       r_middleeast
##  Min.   :-2.58299   Min.   :   0.000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:-0.41515   1st Qu.:   0.325   1st Qu.:0.0000   1st Qu.:0.0000
##  Median : 0.32696   Median :   9.000   Median :0.0000   Median :0.0000
##  Mean   : 0.01364   Mean   :  82.320   Mean   :0.3087   Mean   :0.1007
##  3rd Qu.: 0.72025   3rd Qu.:  42.950   3rd Qu.:1.0000   3rd Qu.:0.0000
##  Max.   : 1.58281   Max.   :4069.100   Max.   :1.0000   Max.   :1.0000
##                     NA's   :4
##     r_europe      r_southamerica       r_asia         country
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Length:298
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   Class :character
##  Median :0.0000   Median :0.0000   Median :0.0000   Mode  :character
##  Mean   :0.2349   Mean   :0.1208   Mean   :0.1678
##  3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##
##    distUNplz            vpd
```

```
##  Min.   : 0.0000   Min.   :  0.00000  
##  1st Qu.: 0.2219   1st Qu.:  0.07722  
##  Median : 0.2956   Median :  0.60506  
##  Mean   : 0.5493   Mean   :  9.86292  
##  3rd Qu.: 0.4608   3rd Qu.:  7.80324  
##  Max.   :15.0552   Max.   :249.36491  
##  NA's   :6
```

```r
min_vio = format(round(min(FM_subcases_per_dip$vpd), 2))
max_vio = format(round(max(FM_subcases_per_dip$vpd), 2))
```

Interestingly we found that violations per diplomat ranges from 0 to 249.36 which further confirms our previous analysis that the number of staff does not correlate to the number of violations. It would otherwise indicate that the average violation would be similar across the countries.

```r
FM_subcases_per_dip$country[FM_subcases_per_dip$vpd == max(FM_subcases_per_dip$vpd)]
```

```
## [1] "KUWAIT"
```

We found that the country that commited more parking violations in Manhattan NY was Kuwait with an outstanding violations of 249 violations per diplomats. We further investigated the variables for Kuwait.

```r
FM_subcases_per_dip[FM_subcases_per_dip$country=="KUWAIT", ]
```

```
##     wbcode prepost  violations       fines mission staff spouse
## 171    KWT     pre 2244.284180 123319.1562       1     9      6
## 172    KWT     pos    1.308244    140.6362       1     9      6
##     gov_wage_gdp pctmuslim majoritymuslim      trade cars_total
## 171           NA      0.85              1 2751607552         17
## 172           NA      0.85              1 2751607552         17
##     cars_personal cars_mission pop1998 gdppcus1998 ecaid milaid region
## 171             5           12 2027000    17874.07     0      0      7
## 172             5           12 2027000    17874.07     0      0      7
##     corruption totaid r_africa r_middleeast r_europe r_southamerica r_asia
## 171  -1.073995      0        0            1        0              0      0
## 172  -1.073995      0        0            1        0              0      0
##     country distUNplz         vpd
## 171  KUWAIT  0.145854 249.3649089
## 172  KUWAIT  0.145854   0.1453604
```

To our surprise, violations of Kuwait pre and post 2002 was astonashing. Its pre violation stood at 2244.2841797 while its post violations stood at 1.3082438 . The violations per diplomat therefore significantly reduced from 249.3649089 to 0.1453604 while all other variables remains the same.

Results

The number of staff does not correlate with the frequency of parking violations in New York Manhattan. Investigation of the average number of violations per diplomats clarified our previous findings that the number of diplomats did not matter. Some countries diplomat committed parking violations as high as 249.36, which rather suggested other underlying causes for such a high frequency per diplomat.

Bibliography and R packages used in this project