Monash University

FIT3152 - Data Analytics

Assignment 1, Semester 1, 2024

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Project: Analysis of country-level predictors of pro-social behaviours to reduce the spread of COVID-19 during the early stages of the pandemic

AI statement: Generative AI was used in this assignment

Task 1: Descriptive analysis and pre-processing

1(a) A condensed extract of the PsyCorona baseline study is contained in the file `PsyCoronaBaselineExtract.csv`.

We start by taking a unique sample of the data set based on my student ID, and attaching the data to the R search path for ease of variable use

```
rm(list = ls())
set.seed(31865224)
cvbase = read.csv("PsyCoronaBaselineExtract.csv")
cvbase <- cvbase[sample(nrow(cvbase), 40000), ]
attach(cvbase)
```

We will take assistance from a few libraries, so let's start by importing those.

```
library(ggplot2)
library(dplyr)
library(tidyr)
```

It is helpful to learn about a dataset's features and properties before working on it.

```
dim(cvbase)
as.data.frame(sapply(cvbase, class))
summary(cvbase, na.rm = TRUE)
```

In this case, we will run the dimensions method, to find out the data frame has 40,000 rows, given we have sampled it to be so when reading it in, and 52 columns.

The only text attributes in the dataframe appear to be `coded_country` and the `Rank Order of Life` columns, while the rest are integer data

According to the codebook extract, every column aside from `employstatus`, `gender`, `age`, `edu`, and `coded_country` contains ordinal numbers representing degrees of agreement for things like age group, education level, and level of agreement. Different `gender`, `age`, and `education` categories are coded by the integer values in their respective columns. Each record may only have a maximum of one employstatus column with a value of 1, indicating the employee's employment status.

We may infer that the numerical attributes have different ranges from the `summary()` output. Survey questions evaluating a two-sided degree of agreement vary from a negative number to its modulus, while those measuring a one-sided degree of agreement go from 1 to a larger positive number, such as 4, 5 or 6.

We are able to use the following, to understand `coded_country` better

```
sort(unique(cvbase$coded_country))
table(cvbase$coded_country)
max(table(cvbase$coded_country))
which(table(cvbase$coded_country) == max(table(cvbase$coded_country)))
```

```
min(table(cvbase$coded_country))
which(table(cvbase$coded_country) == min(table(cvbase$coded_country)))
```

Based on the outputs, there seems to be 110 unique countries inclusive of NA values, with each country having a widely different number of entries, the Croatia having only 222, and host of other countries having much less and much more.

Missing values are present in all columns, however this is the norm as surveys of this nature do not require participants to answer all questions. The `employstatus` columns appear to be the biggest culprit, given each participant will only pick one out of the 10 categories. In this dataframe, `employstatus_3` seems to have the least missing values, while `employstatus_8` has the highest number. Potentially, this could imply that the majority of participants are working 40 hours or more, while a small number of people who are disabled may be out of work.

Another point to note is the mean age group in this dataframe amounts to 2.905, which indicates that the majority of participants are likely to be aged between 35-44 years. This could indicate working-class adults with concise lifestyle, and are studied accordingly to research the outcomes covid had on people.

1(b)

This dataset is relatively tidy and without too many missing values, hence preprocessing should not be required. However, the missing values in the `employstatus` column should be replaced with 0, as it would be easier to transform and process the data in binary format, which might be required for linear regression involving these attributes down the track.

```
cvbase[is.na(cvbase)] <- 0
```

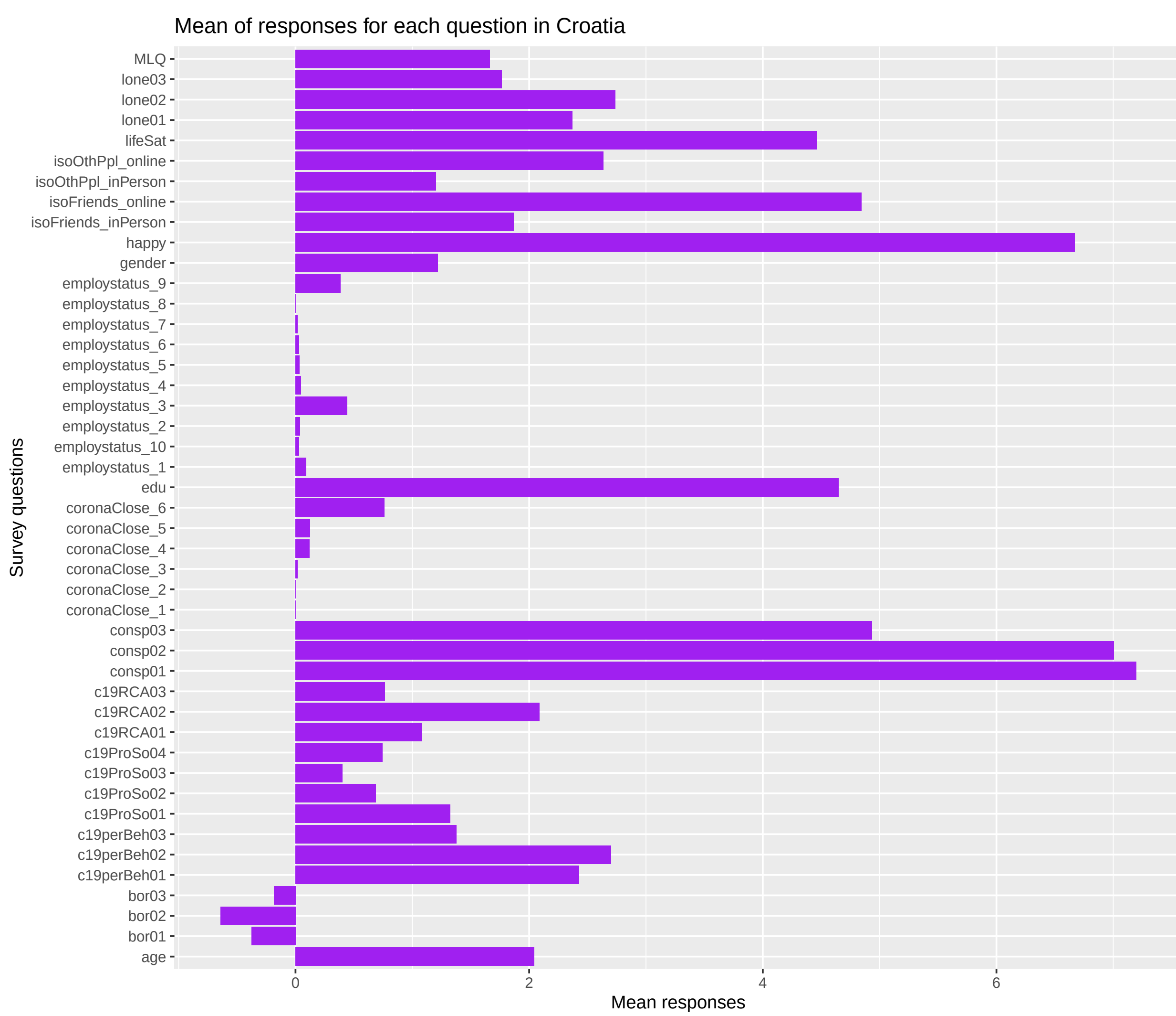
Task 2: Focus country vs all other countries as a group

2(a)

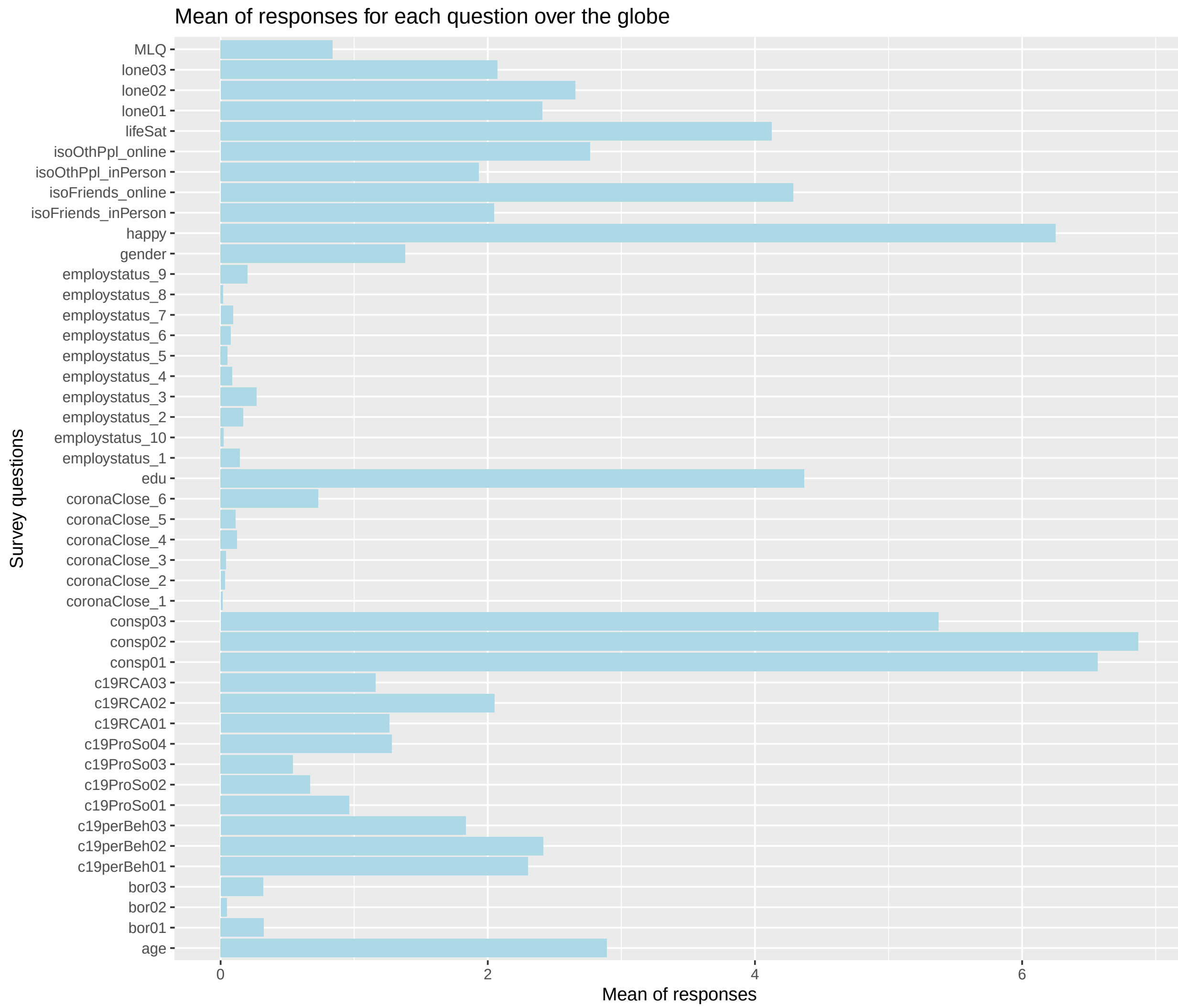
I will be analyzing Croatia in this assignment. We will start by creating bar charts for each group of countries, where the y-axis represents the survey questions, and the x-axis represents the mean of each questions' response. Below, we will create data frames for the mean values utilizing `ggplot2`, excluding non-numerical attributes such as `coded_country`.

```
croatia <- cvbase[cvbase$coded_country == "Croatia", ]
others <- anti_join(cvbase, croatia)

numeric_cols <- sapply(croatia, is.numeric)
means <- colMeans(croatia[, numeric_cols], na.rm = TRUE)

croatia_means <- data.frame(mean = means)

numeric_cols <- sapply(others, is.numeric)
```

```
others_means <- colMeans(others[, numeric_cols], na.rm = TRUE)

others_means <- data.frame(mean = others_means)

croatia_plotted <- ggplot(croatia_means) +
  geom_bar(mapping = aes(x = rownames(croatia_means), y = mean), stat = "identity",
    fill = "purple") +
  coord_flip() +
  labs(x = "Survey questions", y = "Mean responses",
    title = "Mean of responses for each question in Croatia")

world_plotted <- ggplot(others_means) +
  geom_bar(mapping = aes(x = rownames(others_means), y = mean), stat = "identity",
    fill = "lightblue") +
  coord_flip() +
  labs(x = "Survey questions", y = "Mean of responses",
    title = "Mean of responses for each question over the globe")

croatia_plotted
```



```
world_plotted
```



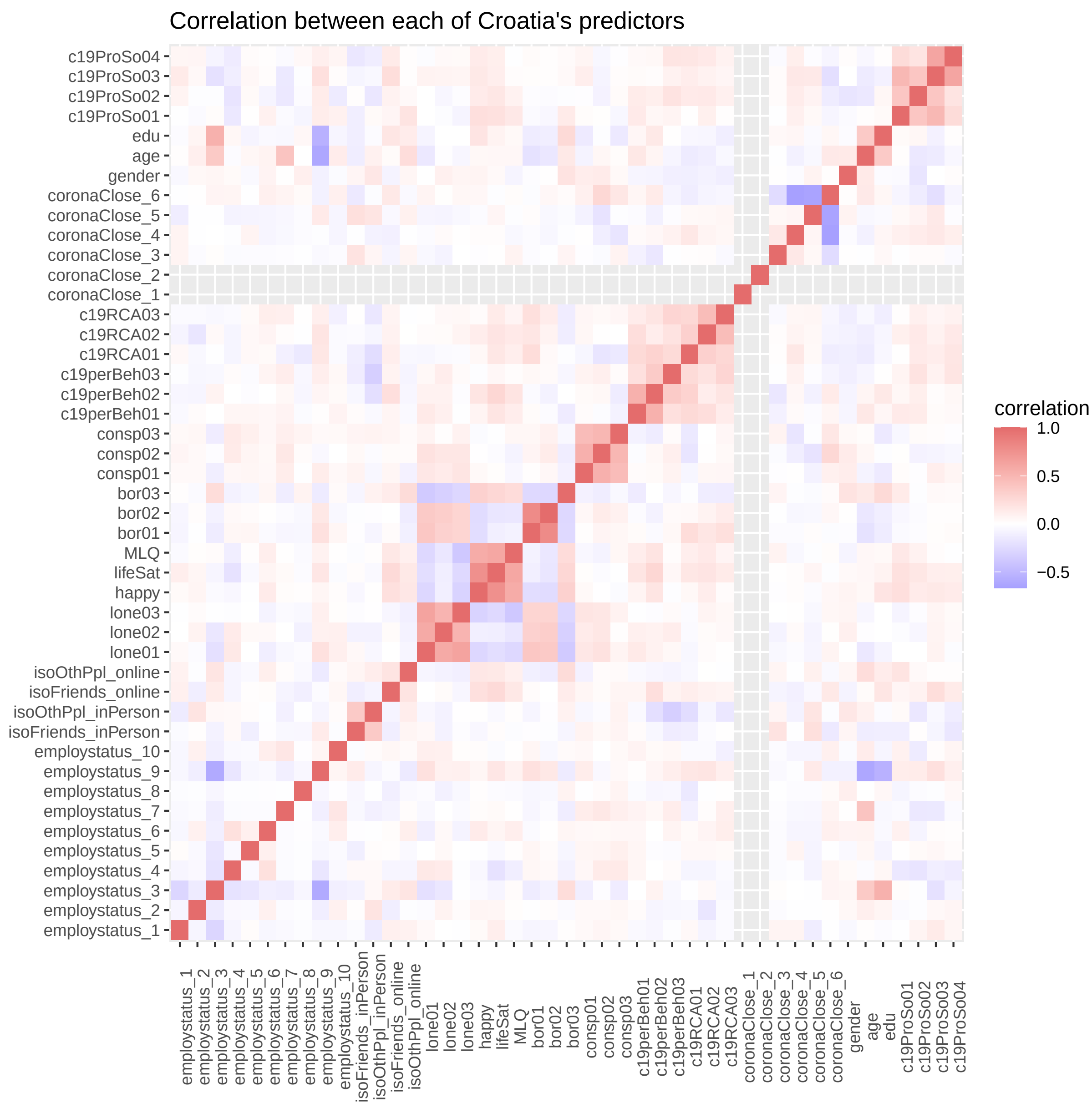
Looking at both graphs of Croatia, and all other countries in comparison, most responses seem to be quite similar, except for Boredom, `bor01`,`bor02` and `bor03`. While the worldwide mean is between 0 (Neither agree nor disagree) and 1 (Somewhat agree), in Croatia, the mean is negative and closer to 1 (Somewhat disagree). This leads us to believe people in Croatia could be less bored than other countries worldwide, albeit slightly. Additionally, there seems to be no Corona Proximity for participants themselves, as well as members of their family in this dataset.

2(b)

Let's start by taking a peek through the correlation of each predictor for pro-social attitude in Croatia. We can visualise the correlation matrix through a heatmap using `cor()`. While Croatia has a lower response rate than other highly populated countries, some operations might not have sufficient data to action.

```
numeric_croatia <- croatia[sapply(croatia, is.numeric)]

croatia_correlation <- cor(numeric_croatia, use = "complete.obs")
```

```r
croatia_melted <- reshape2::melt(croatia_correlation, na.rm = TRUE)

croatia_correlation_plotted <- ggplot(data = croatia_melted, aes(x = Var1, y = Var2, fill = value)) +
  geom_tile() +
  scale_fill_gradient2(low = "#6b74ff", mid = "white", high = "#e46c6c", midpoint = 0) +
  labs(title = "Correlation between each of Croatia's predictors", x = "", y = "",
       fill = "correlation") +
  theme(axis.text.x = element_text(angle = 90))

croatia_correlation_plotted
```



Tiles that are red or blue denote positive or negative correlation, respectively, and turn white as correlation gets closer to zero. Numerous examples of substantial association between predictors can be seen in this heatmap; nevertheless, the portion displaying the correlation between pro-social views and all other traits is quite weak. This suggests that the characteristics might not be a very good indicator of pro-social sentiments in Croatia.

It is possible to determine how survey replies predict the pro-social attitude question through a linear regression model, fitted for each pro-social attitude based on the qualities. Once fitted, it is possible to find the most accurate predictions.

A linear model of each pro-social attitude versus the qualities is fitted by the code that follows. Each model's R-squared, significant predictors possessing a confidence level greater than 99.9%, summarising corresponding coefficients using a function and a for loop. The vectors `predictors` and `each_model` will be utilised in a subsequent table to compare the strong predictors for every model.

```r
predictors <- NULL
each_model <- NULL

model_evaluated <- function(model) {
  rsquared <- summary(model)$r.squared
  adjusted_rsquared <- summary(model)$adj.r.squared
  sig <- which(summary(model)$coefficients[-1, 4] < 0.001) + 1
  predictor <- rownames(summary(model)$coefficients[sig, , drop = FALSE])
  coefficient <- summary(model)$coefficients[sig, 1]

  return(list(rsquared, adjusted_rsquared, predictor, coefficient))
}

fitted_croatia1 <- lm(c19ProSo01 ~ .,
  data = subset(croatia, select = -c(coded_country, c19ProSo02, c19ProSo03, c19ProSo04)))
fitted_croatia2 <- lm(c19ProSo02 ~ .,
  data = subset(croatia, select = -c(coded_country, c19ProSo01, c19ProSo03, c19ProSo04)))
fitted_croatia3 <- lm(c19ProSo03 ~ .,
  data = subset(croatia, select = -c(coded_country, c19ProSo01, c19ProSo02, c19ProSo04)))
fitted_croatia4 <- lm(c19ProSo04 ~ .,
  data = subset(croatia, select = -c(coded_country, c19ProSo01, c19ProSo02, c19ProSo03)))

cat("Pro-social attitudes in Croatia predictors model summary\n\n")
```

```
## Pro-social attitudes in Croatia predictors model summary
```

```r
i <- 1
for (model in list(fitted_croatia1, fitted_croatia2, fitted_croatia3, fitted_croatia4)) {
  cat("C19ProSo0", i, "\n", sep = "")
  collection <- model_evaluated(model)
  cat("R-squared:", collection[[1]], "\n")
  cat("R-squared Adjusted:", collection[[2]], "\n")
  cat("99.9% confidence interval significant predictors:\n")
  cat(collection[[3]], "\n")
  cat("Coefficients of predictors:\n")
  cat(collection[[4]], "\n")
  cat("\n")
  for (each in collection[[3]]) {
    each_model <- c(each_model, paste0("Croatia_C19ProSo0", i))
  }
  predictors <- c(predictors, collection[[3]])
  i <- i + 1
}
```

```
## C19ProSo01
## R-squared: 0.4686053
## R-squared Adjusted: 0.2519858
## 99.9% confidence interval significant predictors:
##
## Coefficients of predictors:
##
##
## C19ProSo02
## R-squared: 0.3355854
## R-squared Adjusted: 0.06474127
## 99.9% confidence interval significant predictors:
##
## Coefficients of predictors:
##
##
## C19ProSo03
## R-squared: 0.4872678
## R-squared Adjusted: 0.278256
## 99.9% confidence interval significant predictors:
## isoFriends_online
## Coefficients of predictors:
## 0.1795645
##
## C19ProSo04
## R-squared: 0.3617789
## R-squared Adjusted: 0.1016124
## 99.9% confidence interval significant predictors:
## rankOrdLife_4D
## Coefficients of predictors:
## 6.462742
```

`C19ProSo03` has the greatest adjusted R-squared at 0.278256 out of all the models, indicating that the responses best predict it. `isoFriends_online` is its best predictor. The `C19ProSo04` model has the least adjusted R-squared value at 0.1016124 , and `rankOrdLife_4D` is its best predictor.

The fact that the majority of the survey items are deemed subjective makes the models' arguably low R-squared values predictable. For instance, different individuals interpret financial hardship differently and perceive various levels of serenity differently. Since Croatia is a moderately populated nation with a wide range of living standards, its several regions are like independent nations with their own economies, healthcare systems, and general levels of satisfaction. Because of this, it is challenging to forecast the pro-social attitude reactions with consistency.

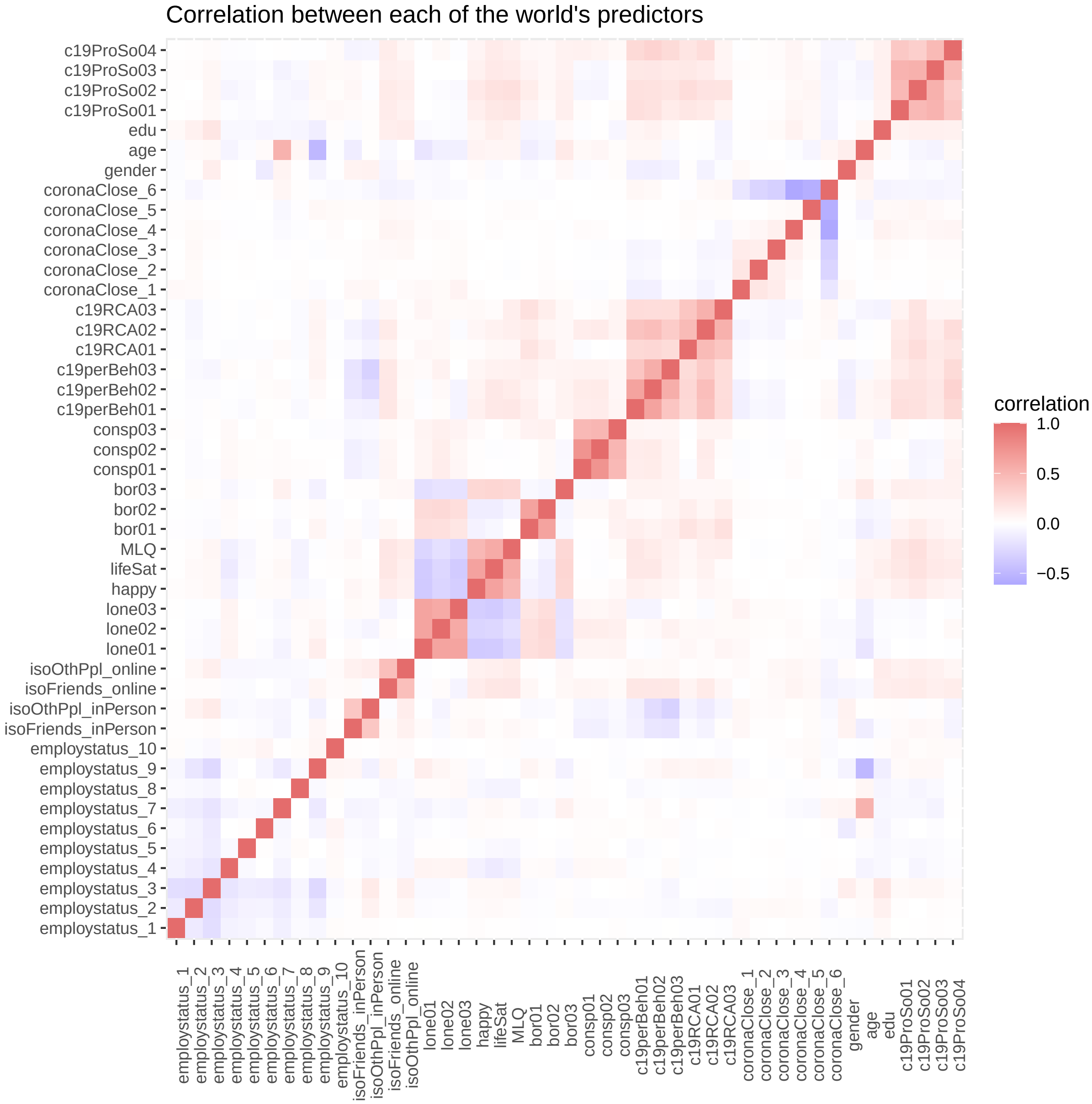
Although each model has a unique set of important predictors, some predictors can be regarded as generally more reliable because they are more frequently found in all of the models. The best illustration would be `c19NormShould`, a highly predictive variable for each of the models. During a pandemic, someone who is willing to assist society would want the best for it and would counsel individuals to isolate themselves and avoid social interactions.. The Centers for Disease Control and Prevention (CDC) in Croatia recommend these steps to stop the spread of viruses, and since Croatia is a developed country with a highly educated populace, people who aspire to be pro-social generally abide by these recommendations. Conversely, a person devoid of pro-social attitudes would not care about adhering to new rules or showing any interest in societal behaviors. Those who disagree with social distancing policies and believe that doing so benefits society as a whole may also have an impact on the predictive power of `c19NormShould`. During the epidemic, lock down protests were prevalent in Croatia, demonstrating the validity of this viewpoint.

`disc02`, `MLQ`, and `trustGovState` are additional variables that predict three of the models effectively. People are more likely to be pro-social if they care about the future of society, if they have a purpose in life, and if they think society can come to an agreement on how to handle the pandemic.

2(c)

The previous code blocks for 2(b) are modified, but with the `rem` data set instead of `croatia`, to produce a similar correlation matrix for the rest of the world. To keep the report concise, variants of code that have been modified further on, can be found in the **Appendix**.

```
global_correlation_plot
```



When we compare the two heatmaps we currently have, we see that `cro_cor_plot` has tiles coloured in a deeper shade of red, which suggests a larger overall correlation between the predictors. Apart from having lighter tiles, `rem_cor_plot` appears "cleaner" due to a reduced dispersion of coloured tiles. However, since the subsections in both plots appear fairly similar, focusing on the heatmap subsections that illustrate the association between pro-social attitudes and all other features, We can hypothesise that pro-social views should be predicted with somewhat equivalent performance by the attributes for both sets of data.

```
## Pro-social attitudes in the world predictors model summary

## C19ProSo01
## R-squared: 0.1280411
## Adjusted R-squared: 0.12646
## 99.9% confidence interval significant predictors:
## employstatus_6 employstatus_7 employstatus_8 employstatus_10 isoFriends_inPerson isoOthPpl_inPerson i
## Coefficients of predictors:
## -0.09356577 -0.2272962 -0.1897203 0.3730428 0.01719855 0.02667376 0.01609172 0.01721033 0.0606518 -0
##
## C19ProSo02
## R-squared: 0.1766909
## Adjusted R-squared: 0.1751979
## 99.9% confidence interval significant predictors:
## employstatus_3 employstatus_4 employstatus_5 employstatus_8 employstatus_10 isoFriends_inPerson isoFr
## Coefficients of predictors:
## 0.1072481 -0.1977689 -0.1317748 -0.3161566 0.2091906 0.03416122 0.0152765 0.02820841 0.05811839 -0.0
##
## C19ProSo03
## R-squared: 0.1199772
## Adjusted R-squared: 0.1183814
## 99.9% confidence interval significant predictors:
## employstatus_3 employstatus_7 employstatus_10 isoFriends_inPerson isoOthPpl_inPerson isoOthPpl_online
## Coefficients of predictors:
## 0.1555728 -0.2152103 0.3369801 0.02274039 0.02160123 0.02621581 0.066345 0.09423445 0.0588311 0.0282
##
## C19ProSo04
## R-squared: 0.17178
## Adjusted R-squared: 0.1702782
## 99.9% confidence interval significant predictors:
## employstatus_2 employstatus_3 employstatus_10 isoFriends_online lone02 lone03 lifeSat MLQ bor02 bor03
## Coefficients of predictors:
## 0.09869336 0.1272541 0.2820308 0.01248981 0.03724033 0.03827886 0.07587075 0.02828067 0.02557799 0.0
```

All four models had adjusted R-squared somewhere between 0.12 and 0.17, pointing to a smaller range than the comparable one for the Croatia data set (0.06 - 0.49), according to the summary for the rest of the world. The models' predictors are significantly more important than those of the `croatia` models. The four models are well predicted by `disc02`, `lifeSat`, `c19NormShould`, `c19NormDo`, and `trustGovState`. The majority of the predictors that performed well in all four of the `croatia` models, `c19NormShould`, `disc02`, and `trustGovState` are included in this set. As was already said, Croatia's sheer vastness and diversity make it seem like a collection of independent nations. It follows that strong predictors for Croatia would also apply to other nations collectively.

The table below displays the results of the strongest predictors for each pro-social behaviour for Croatia and the rest of the globe.

```r
tables_combined <- table(predictors = predictors, models = each_model)

tables_combined <- tables_combined[, c("Croatia_C19ProSo03",
```

```
  "Croatia_C19ProSo04", "RoW_C19ProSo01", "RoW_C19ProSo02", "RoW_C19ProSo03",
  "RoW_C19ProSo04")]

tables_combined_plotted <- ggplot(data = as.data.frame(tables_combined)) +
  geom_tile(mapping = aes(x = models, y = predictors, fill = Freq, colour = "black")) +
  scale_fill_gradientn(colours = c("pink", "green")) +
  theme(legend.position = "none") +
  scale_x_discrete(position = "top") +
  scale_y_discrete(limits = rev) +
  labs(x = "Models", y = "Predictors",
    title = "Significant predictors for individual models")

tables_combined_plotted
```

Task 3: Focus country vs cluster of similar countries

3(a)

Some additional data is collected from external sources to supplement the indicators available in the sources mentioned in the references. Eight indicators make up the final data table I have compiled (in **Appendix**) for use in clustering: `HDI`, `GHS`, `freedom`, `political_stability`, `happiness`, `total_vax_per_hundred`, `total_cases_per_mil`, and `total_deaths_per_mil`. The **Appendix** contains information and explanations regarding each indicator as well as its sources.

Using k-means clustering, nations that are comparable to Croatia are found. For the `kmeans()` function to function, countries with NA values must first be eliminated. This has no bearing on our findings because the majority of these nations—such as Afghanistan and Syria—do not initially appear in the baseline data and differ greatly from Croatia in terms of development and data transparency. After scaling the data, we use a few random beginnings to carry out K-means clustering.

```
external <- read.csv("task3.csv")
cleaned_external <- na.omit(external)
cleaned_external[, 2:9] <- scale(cleaned_external[, 2:9])

kfit <- kmeans(cleaned_external[, 2:9], round(nrow(cleaned_external) / 5), nstart = 15)
clusters <- data.frame(country = cleaned_external[[1]], cluster = kfit$cluster)

target <- filter(clusters, country == "Croatia")$cluster
similar <- filter(clusters, cluster == target)

similar
```

```
##      country cluster
## 42   Croatia      24
## 76   Hungary      24
## 137   Poland      24
## 140  Romania      24
## 155 Slovakia      24
```

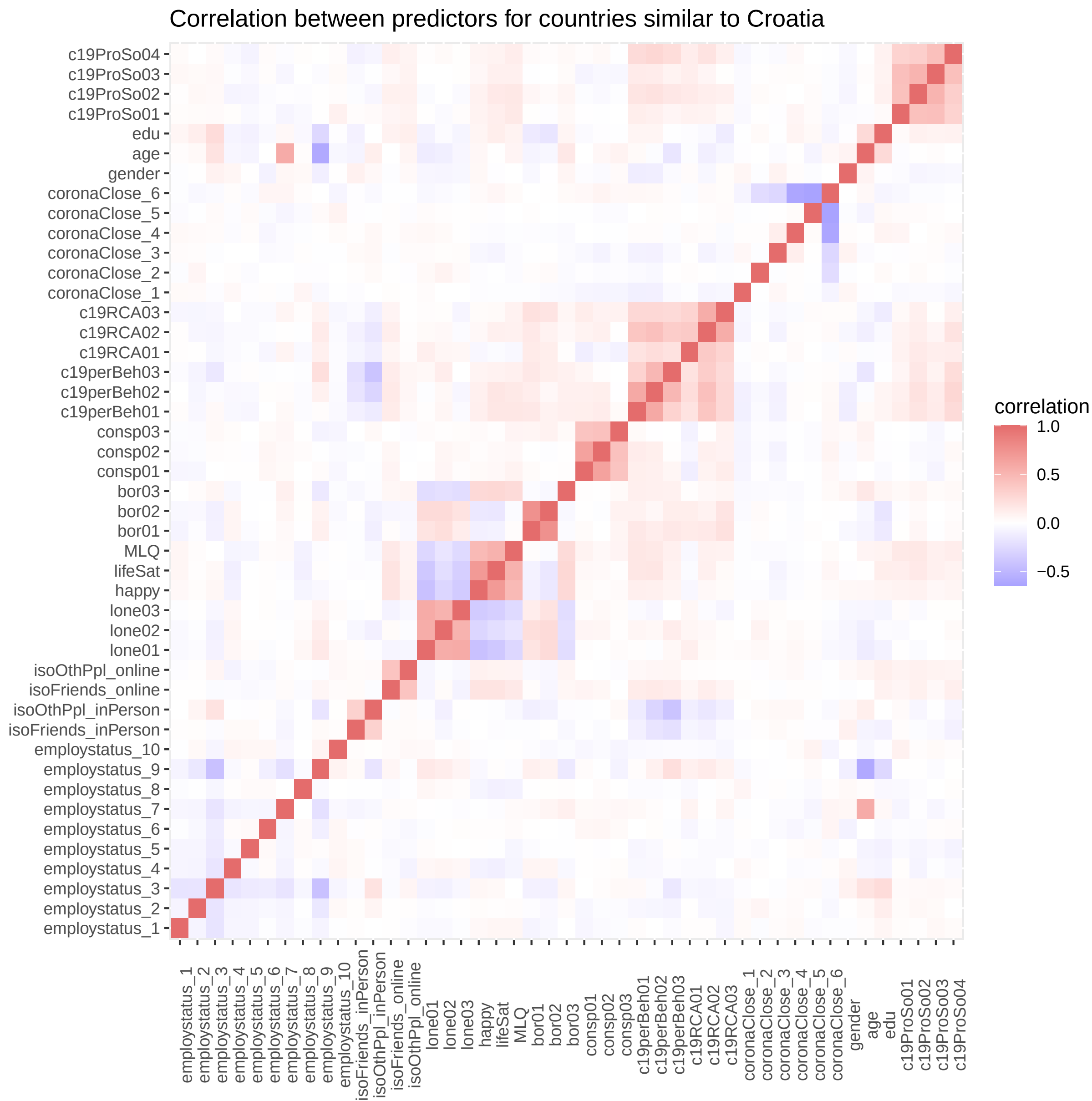
The clustering indicates that Hungary, Poland, Romania and Slovakia are comparable to Croatia.

3(b)

After removing the data from Croatia, the baseline data of the cluster's member nations are initially extracted by inner joining `cvbase` and `similar`. Finally, we visualize the given correlation matrix, in line with `croatia` and the rest of the globe.

```
colnames(similar)[colnames(similar) == "country"] <- "coded_country"
common <- merge(cvbase, similar, by = "coded_country", all = FALSE)
common <- common[, -ncol(common)]
clustered <- filter(common, coded_country != "Croatia")

non_numeric_columns <- sapply(clustered, function(x) !is.numeric(x))
clustered_numeric <- subset(clustered, select = !non_numeric_columns)

clustered_correlation_matrix <- cor(clustered_numeric, use = "complete.obs")
clustered_melted <- reshape2::melt(clustered_correlation_matrix)
```

```
clustered_correlation_plotted
```



This heat map's scatter of colored tiles is identical to the Croatia heat map's, showing how similar these two nations are. In comparison to the previous plots, the portion of tiles displaying the correlation between predictors and pro-social views is generally darker, suggesting the predictors related to the cluster in question may perform positively in terms of prediction than the data from the previous two groups.

Finally, repeating the code fragments from Task 2, b and c, we can output a structured summary for all models in order to determine how respondent answers can be a significant predictor of pro-social views pertaining to the similar countries cluster in question.

```
## Model Summary for countries similar to the Croatia to predict pro-social attitudes

## C19ProSo01
```

```
## R-squared: 0.1019308
## Adjusted R-squared: 0.07645638
## 99.9% confidence interval significant predictors:
## employstatus_10 MLQ rankOrdLife_3B c19RCA01
## Coefficients of predictors:
## 0.6937677 0.1364176 -0.6291484 0.05595581
##
## C19ProSo02
## R-squared: 0.1275736
## Adjusted R-squared: 0.1028265
## 99.9% confidence interval significant predictors:
## MLQ c19RCA01
## Coefficients of predictors:
## 0.1080792 0.07625105
##
## C19ProSo03
## R-squared: 0.1031383
## Adjusted R-squared: 0.07769807
## 99.9% confidence interval significant predictors:
## MLQ rankOrdLife_3C c19RCA01
## Coefficients of predictors:
## 0.09845237 -0.5655349 0.08508227
##
## C19ProSo04
## R-squared: 0.1595349
## Adjusted R-squared: 0.1356944
## 99.9% confidence interval significant predictors:
## MLQ rankOrdLife_1B rankOrdLife_1C rankOrdLife_1D rankOrdLife_1F rankOrdLife_3B c19perBeh01 c19perBeh0
## Coefficients of predictors:
## 0.0850501 1.498947 1.385919 1.365358 1.5909 -0.68414 0.1338745 0.1736953 0.1314914
```

Based on the results, the models for these comparable nations typically have adjusted R-squared values that are comparable to those of Croatia and all other nations combined. Similar to the Croatia models, `C19ProSo04` seems to have the greatest adjusted R-squared value (0.1356944). Except for `C19ProSo04`, which has significant predictors including `disc02`, `MLQ`, `c19NormShould` and `c19IsPunish`, none of these models, in contrast to the preceding eight models, had significant predictors with p-values less than 0.001. In the Croatia model, `disc02` is also a very good predictor for `C19ProSo04`, but not for `PFS02`. However, `disc02`, `MLQ`, `c19NormShould` and `c19IsPunish` are all significant predictors over the rest of the globe model for `C19ProSo04`.

Consequently, the prediction of qualities for this cluster of countries is in no way particularly better off than Croatia or the rest of the globe, with comparable R-squared values and predictors with generally lower confidence intervals. The previously reported large correlation may have been insignificant sample size rather than representing genuine statistically significant links between pro-social attitudes and qualities.

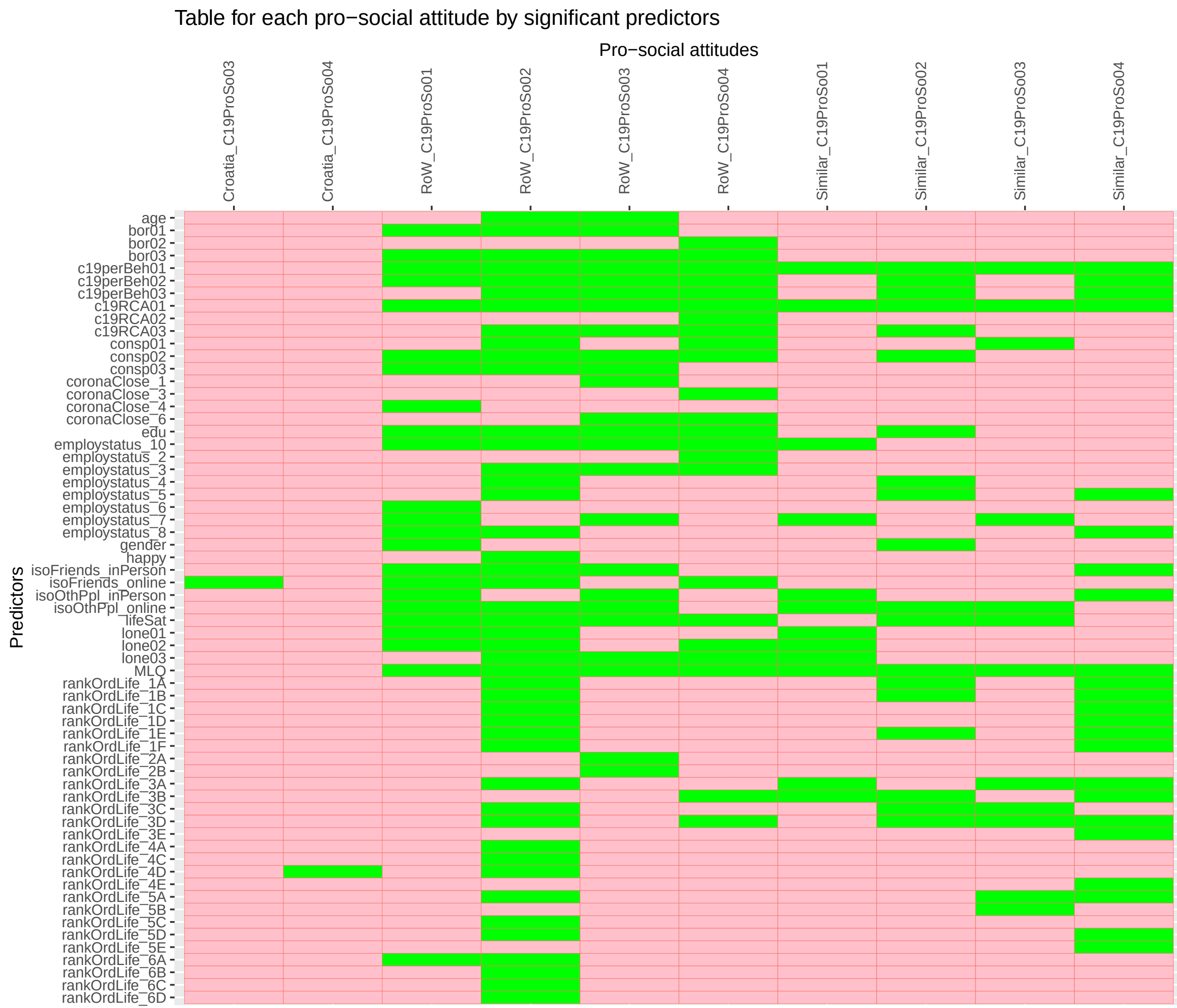
We can define a strong predictor in relation to a model's total p-values for comparative purposes. For these novel cluster models, we characterize a strong predictor as one with a p-value of less than 0.05, which is a widely accepted threshold. A new visualization table is constructed and the `model_evaluated` function is changed in line with the model.

```
## Model Summary for countries similar to the Croatia to predict pro-social attitudes
```

```
## C19ProSo01
## R-squared: 0.1019308
```

```
## Adjusted R-squared: 0.07645638
## 95% confidence interval significant predictors:
## employstatus_7 employstatus_10 isoOthPpl_inPerson isoOthPpl_online lone01 lone02 lone03 MLQ rankOrdLi
## Coefficients of predictors:
## -0.4443775 0.6937677 0.03384447 0.033907 0.06722975 -0.0930139 0.09173 0.1364176 -0.5174174 -0.629148
##
## C19ProSo02
## R-squared: 0.1275736
## Adjusted R-squared: 0.1028265
## 95% confidence interval significant predictors:
## employstatus_4 employstatus_5 isoOthPpl_online lifeSat MLQ consp02 rankOrdLife_1A rankOrdLife_1B ranl
## Coefficients of predictors:
## -0.2919775 -0.3600833 0.03217282 0.1372649 0.1080792 -0.04087629 1.069375 1.125655 0.8700702 -0.4339
##
## C19ProSo03
## R-squared: 0.1031383
## Adjusted R-squared: 0.07769807
## 95% confidence interval significant predictors:
## employstatus_7 isoOthPpl_online lifeSat MLQ consp01 rankOrdLife_3A rankOrdLife_3C rankOrdLife_3D ranl
## Coefficients of predictors:
## -0.5393024 0.03719592 0.09921346 0.09845237 -0.04105437 -0.5538729 -0.5655349 -0.3214164 -0.4687776
##
## C19ProSo04
## R-squared: 0.1595349
## Adjusted R-squared: 0.1356944
## 95% confidence interval significant predictors:
## employstatus_5 employstatus_8 isoFriends_inPerson isoOthPpl_inPerson MLQ rankOrdLife_1A rankOrdLife_
## Coefficients of predictors:
## -0.4926586 0.5835967 -0.02775915 0.03682043 0.0850501 1.325203 1.498947 1.385919 1.365358 1.238381 1
```

```
summary_table_visualised_2
```



We see that strongest predictors being distributed between the models of countries that are similar is closer to the Croatian models, with a few shared significant predictors (i.e., appearing quite as "sparse" as the Croatia models). Given more comparable p-values, the models from the group of all other nations have a great deal more significant predictors in common with the Croatian models. These models do, however, also contain a large number of powerful predictors that are absent from the Croatian models. Consequently, the group of comparable nations may provide a better fit to the critical characteristics needed to predict pro-social sentiments. The smaller the confidence level, as well as less common strongest predictors included throughout those models may become insignificant with additional study or a larger sample size.

One explanation could be that, despite their similarities to Croatia, each country in the cluster varies slightly from the others in terms of socioeconomic factors that are not taken into account by the clustering indicators.. Their collective performance in forecasting pro-social attitudes differs substantially from Croatia alone when these small variations are taken into account. However, because Croatia's politics, culture, and other aspects of society are complicated, much like those of a group of many countries, its models have many strong predictors in common with the models pertaining to the cluster of all countries. The models may report multiple significant predictors that are not important because the cluster of all other countries could be too complicated or big.

Appendix

References

I acknowledge the use of [1] Grammarly (https://app.grammarly.com/) [2] to refine the academic language and accuracy of my own work. On 6 April 2024 I submitted my entire report with the instruction to [3] “Improve the academic tone and accuracy of language, including grammatical structures, punctuation and vocabulary”. [4] The output was then modified further to better represent my own tone and style of writing.

I acknowledge the use of [1] ChatGPT (https://chat.openai.com/) to [2] generate materials for background research and self-study in the drafting of this assessment. I entered the following prompts on 30 March 2024:

[3] Write basic R code skeleton to use ggplot to plot a correlation matrix from a data set [3] Write basic R code skeleton to fit a linear model

[4] The output from the generative artificial intelligence was adapted and modified for the final response.

`cvbase` head, 1(b)

```r
head(cvbase)
```

```
##       employstatus_1 employstatus_2 employstatus_3 employstatus_4
## 21475              0              1              0              0
## 3823               0              0              0              1
## 57606              0              1              0              0
## 49874              0              0              0              0
## 16726              1              1              1              0
## 23113              0              0              0              0
##       employstatus_5 employstatus_6 employstatus_7 employstatus_8
## 21475              0              0              0              0
## 3823               0              0              0              0
## 57606              0              0              0              0
## 49874              0              0              1              0
## 16726              0              0              0              0
## 23113              0              0              1              0
##       employstatus_9 employstatus_10 isoFriends_inPerson isoOthPpl_inPerson
## 21475              0               0                   0                  2
## 3823               0               0                   1                  0
## 57606              0               0                   1                  2
## 49874              0               0                   1                  1
## 16726              0               0                   3                  2
## 23113              0               0                   0                  0
##       isoFriends_online isoOthPpl_online lone01 lone02 lone03 happy lifeSat MLQ
## 21475                 6                1      1      1      1     9       5   2
## 3823                  6                0      3      3      2     6       2   1
## 57606                 4                4      2      2      1     7       4   1
## 49874                 7                3      2      3      2     8       5   0
## 16726                 7                4      3      3      4     9       5   3
## 23113                 7                0      4      5      5     4       2   0
##       bor01 bor02 bor03 consp01 consp02 consp03 rankOrdLife_1 rankOrdLife_2
## 21475     1     1    -2       7       8       0             F             D
## 3823     -2    -1     1       6       1       2             C             E
## 57606     0     0     0       8       8       2             D             E
## 49874    -2    -2     3      10       8       0             F             D
## 16726     2     1     3       6       8       6             0             0
## 23113     0     0    -3      10      10       7             E             D
```

```
##       rankOrdLife_3 rankOrdLife_4 rankOrdLife_5 rankOrdLife_6 c19perBeh01
## 21475             E             C             A             B           3
## 3823              F             D             A             B           3
## 57606             F             C             A             B           3
## 49874             E             C             A             B           3
## 16726             0             0             0             0           3
## 23113             F             B             A             C           3
##       c19perBeh02 c19perBeh03 c19RCA01 c19RCA02 c19RCA03 coronaClose_1
## 21475           3           3        0        0       -2             0
## 3823            2           2        0        3        2             0
## 57606           3           1        1        2       -1             0
## 49874           3           3        0        3        1             0
## 16726           3           3        3        3        3             0
## 23113           3           3       -3       -3       -3             0
##       coronaClose_2 coronaClose_3 coronaClose_4 coronaClose_5 coronaClose_6
## 21475             1             0             1             1             0
## 3823              0             0             0             0             1
## 57606             0             0             0             0             1
## 49874             0             0             0             0             1
## 16726             1             0             0             0             0
## 23113             0             0             0             0             1
##       gender age edu coded_country c19ProSo01 c19ProSo02 c19ProSo03 c19ProSo04
## 21475      1   3   5         Spain          2          2         -1          3
## 3823       1   3   6        Greece          1         -1          2          2
## 57606      2   4   4       Germany          2          2          1          1
## 49874      1   5   4        Canada         -2          1          1          3
## 16726      1   2   6     Indonesia          3          3          3          3
## 23113      2   6   5        France          0         -3         -3          0
```

others Correlation matrix, 2(c)

```r
others <- anti_join(cvbase, croatia)

numeric_others <- others[sapply(others, is.numeric)]

global_correlation <- cor(numeric_others, use = "complete.obs")

global_melted <- reshape2::melt(global_correlation)

global_correlation_plot <- ggplot(data = global_melted) +
  geom_tile(mapping = aes(x = Var1, y = Var2, fill = value)) +
  scale_fill_gradient2(low = "#6b74ff", mid = "white", high = "#e46c6c", midpoint = 0) +
  labs(title = "Correlation between each of the world's predictors", x = "", y = "",
    fill = "correlation") +
  theme(axis.text.x = element_text(angle = 90))
```

others models, 2(c)

```r
fitted_rest1 <- lm(c19ProSo01 ~ .,
  data = subset(others, select = -c(coded_country, c19ProSo02, c19ProSo03, c19ProSo04)))
fitted_rest2 <- lm(c19ProSo02 ~ .,
  data = subset(others, select = -c(coded_country, c19ProSo01, c19ProSo03, c19ProSo04)))
fitted_rest3 <- lm(c19ProSo03 ~ .,
```

```r
  data = subset(others, select = -c(coded_country, c19ProSo01, c19ProSo02, c19ProSo04)))
fitted_rest4 <- lm(c19ProSo04 ~ .,
  data = subset(others, select = -c(coded_country, c19ProSo01, c19ProSo02, c19ProSo03)))

cat("Pro-social attitudes in the world predictors model summary\n\n")
res_counter <- 1
for (model in list(fitted_rest1, fitted_rest2, fitted_rest3, fitted_rest4)) {
  cat("C19ProSo0", res_counter, "\n", sep = "")
  res <- model_evaluated(model)
  cat("R-squared:", res[[1]], "\n")
  cat("Adjusted R-squared:", res[[2]], "\n")
  cat("99.9% confidence interval significant predictors:\n")
  cat(res[[3]], "\n")
  cat("Coefficients of predictors:\n")
  cat(res[[4]], "\n")
  cat("\n")
  for (pred in res[[3]]) {
    each_model <- c(each_model, paste0("RoW_C19ProSo0", res_counter))
  }
  predictors <- c(predictors, res[[3]])
  res_counter <- res_counter + 1
}
```

Clustering data, 3(a)

```r
external
```

```
##                            country   HDI  GHS freedom political_stability
## 1                      Afghanistan 0.478 28.8      NA               -2.53
## 2                          Albania 0.796 45.0    8.14                0.11
## 3                          Algeria 0.745 26.2    5.26               -0.88
## 4                          Andorra 0.858 34.7      NA                1.63
## 5                           Angola 0.586 29.1    6.09               -0.71
## 6              Antigua and Barbuda 0.788 30.0      NA                0.96
## 7                        Argentina 0.842 54.4    7.38               -0.11
## 8                          Armenia 0.759 61.8    8.20               -0.84
## 9                        Australia 0.951 71.1    8.84                0.85
## 10                         Austria 0.916 56.9    8.67                0.91
## 11                      Azerbaijan 0.745 34.7    6.16               -0.85
## 12                         Bahamas 0.812 30.1    8.22                0.88
## 13                         Bahrain 0.875 36.3    5.73               -0.51
## 14                      Bangladesh 0.661 35.5    5.75               -0.97
## 15                        Barbados 0.790 34.9    7.92                1.12
## 16                         Belarus 0.808 43.9    6.73               -0.74
## 17                         Belgium 0.937 59.3    8.61                0.61
## 18                          Belize 0.683 29.7    7.64                0.46
## 19                           Benin 0.525 25.4    7.32               -0.30
## 20                          Bhutan 0.666 39.8    6.86                0.97
## 21                         Bolivia 0.692 29.9    6.94               -0.32
## 22          Bosnia and Herzegovina 0.780 35.4    7.54               -0.38
## 23                        Botswana 0.693 33.6    7.90                0.98
## 24                          Brazil 0.754 51.2    7.22               -0.49
## 25                          Brunei 0.829 43.5    6.46                1.17
```

```
## 26                   Bulgaria 0.795 59.9    8.08                  0.46
## 27               Burkina Faso 0.449 29.8    6.85                 -1.64
## 28                    Burundi 0.426 22.1    5.02                 -1.36
## 29                 Cape Verde 0.662 34.1      NA                  0.90
## 30                   Cambodia 0.593 31.1    6.47                 -0.13
## 31                   Cameroon 0.576 28.6    5.63                 -1.41
## 32                     Canada 0.936 69.8    8.85                  0.94
## 33   Central African Republic 0.404 18.6    5.62                 -2.10
## 34                       Chad 0.394 23.9    5.57                 -1.34
## 35                      Chile 0.855 56.2    8.44                  0.06
## 36                      China 0.768 47.5    5.57                 -0.48
## 37                   Colombia 0.752 53.2    7.01                 -0.91
## 38                    Comoros 0.558 24.9    6.07                 -0.23
## 39                      Congo 0.571 26.3    5.55                 -0.61
## 40                 Costa Rica 0.809 40.8    8.25                  0.87
## 41              Côte d'Ivoire 0.550 31.2    6.90                 -0.95
## 42                    Croatia 0.858 48.8    8.16                  0.71
## 43                       Cuba 0.764 30.5      NA                  0.43
## 44                     Cyprus 0.896 41.9    8.42                  0.44
## 45             Czech Republic 0.889 52.8    8.61                  0.96
## 46                 D.R. Congo 0.479 26.1    5.62                 -1.61
## 47                    Denmark 0.948 64.4    8.98                  0.95
## 48                   Djibouti 0.509 25.2    5.84                 -0.71
## 49                   Dominica 0.720 26.4      NA                  1.39
## 50         Dominican Republic 0.767 34.5    7.88                  0.14
## 51                    Ecuador 0.740 50.8    7.43                 -0.27
## 52                      Egypt 0.731 28.0    4.49                 -1.02
## 53                El Salvador 0.675 40.8    7.39                 -0.21
## 54          Equatorial Guinea 0.596 17.4      NA                 -0.29
## 55                    Eritrea 0.492 21.4      NA                 -1.01
## 56                    Estonia 0.890 55.5    8.91                  0.76
## 57                   Eswatini 0.597 29.3    5.79                 -0.03
## 58                   Ethiopia 0.498 37.8    5.95                 -2.07
## 59                       Fiji 0.730 25.8    7.36                  0.67
## 60                    Finland 0.940 70.9    8.85                  0.98
## 61                     France 0.903 61.9    8.34                  0.37
## 62                      Gabon 0.706 21.8    6.80                 -0.09
## 63                     Gambia 0.500 28.7    6.88                  0.18
## 64                    Georgia 0.802 52.6    8.20                 -0.42
## 65                    Germany 0.942 65.5    8.73                  0.76
## 66                      Ghana 0.632 34.3    7.49                  0.07
## 67                     Greece 0.887 51.5    7.86                  0.15
## 68                    Grenada 0.795 26.7      NA                  1.04
## 69                  Guatemala 0.627 29.1    7.63                 -0.39
## 70                     Guinea 0.465 26.8    5.82                 -0.97
## 71              Guinea-Bissau 0.483 21.4      NA                 -0.28
## 72                     Guyana 0.714 30.8    7.49                 -0.14
## 73                      Haiti 0.535 30.4    7.21                 -1.10
## 74                   Honduras 0.621 26.2    7.09                 -0.61
## 75           Hong Kong S.A.R. 0.952   NA    8.41                  0.26
## 76                    Hungary 0.846 54.4    7.73                  0.86
## 77                    Iceland 0.959 48.5    8.77                  1.37
## 78                      India 0.633 42.8    6.39                 -0.62
## 79                  Indonesia 0.705 50.4    7.10                 -0.51
```

```
## 80                              Iran 0.774 36.5    4.53                -1.62
## 81                              Iraq 0.686 24.0    5.02                -2.40
## 82                           Ireland 0.945 55.3    8.90                 0.86
## 83                            Israel 0.919 47.2    7.66                -1.06
## 84                             Italy 0.895 51.9    8.49                 0.58
## 85                           Jamaica 0.709 31.8    7.91                 0.22
## 86                             Japan 0.925 60.5    8.73                 1.03
## 87                            Jordan 0.720 42.8    6.91                -0.28
## 88                        Kazakhstan 0.811 46.1    6.77                -0.25
## 89                             Kenya 0.575 38.8    6.73                -1.09
## 90                          Kiribati 0.624 26.2      NA                 1.19
## 91                            Kuwait 0.831 36.8    6.34                 0.30
## 92                        Kyrgyzstan 0.692 42.4    7.18                -0.43
## 93                              Laos 0.607 34.8    5.85                 0.73
## 94                            Latvia 0.863 61.9    8.67                 0.69
## 95                           Lebanon 0.706 33.4    6.76                -1.49
## 96                           Lesotho 0.514 30.9    7.01                -0.22
## 97                           Liberia 0.481 35.7    6.81                -0.24
## 98                             Libya 0.718 25.3    5.05                -2.37
## 99                     Liechtenstein 0.935 46.4      NA                 1.64
## 100                        Lithuania 0.875 59.5    8.68                 0.82
## 101                       Luxembourg 0.930 48.4    8.80                 1.21
## 102                       Madagascar 0.501 30.4    7.02                -0.64
## 103                           Malawi 0.512 28.5    6.99                -0.11
## 104                         Malaysia 0.803 56.4    7.17                 0.14
## 105                         Maldives 0.747 32.0      NA                 0.50
## 106                             Mali 0.428 29.0    6.25                -2.35
## 107                            Malta 0.918 40.2    8.45                 0.97
## 108                 Marshall Islands 0.639 24.6      NA                 0.61
## 109                       Mauritania 0.556 26.2    5.73                -0.67
## 110                        Mauritius 0.802 39.7    8.07                 0.86
## 111                           Mexico 0.758 57.0    6.92                -0.64
## 112                       Micronesia 0.628 28.5      NA                 1.11
## 113                          Moldova 0.767 41.0    7.68                -0.21
## 114                         Mongolia 0.739 41.0    8.00                 0.65
## 115                       Montenegro 0.832 44.1    7.88                -0.15
## 116                          Morocco 0.683 33.6    5.90                -0.40
## 117                       Mozambique 0.446 30.4    6.80                -1.23
## 118                          Myanmar 0.585 38.3    5.78                -2.07
## 119                          Namibia 0.615 30.3    7.56                 0.55
## 120                            Nepal 0.602 34.0    7.12                -0.24
## 121                      Netherlands 0.941 64.7    8.78                 0.92
## 122                      New Zealand 0.937 62.5    9.01                 1.44
## 123                        Nicaragua 0.667 36.3    6.24                -0.47
## 124                            Niger 0.400 28.7    6.41                -1.62
## 125                          Nigeria 0.535 38.0    6.28                -1.78
## 126                  North Macedonia 0.770 42.2    7.75                 0.12
## 127                           Norway 0.961 60.2    8.76                 1.10
## 128                             Oman 0.816 39.1    5.92                 0.51
## 129                         Pakistan 0.544 30.4    5.63                -1.67
## 130                            Palau 0.767 25.5      NA                 0.95
## 131                        Palestine 0.715   NA      NA                   NA
## 132                           Panama 0.805 53.5    8.12                 0.29
## 133                 Papua New Guinea 0.558 25.0    7.17                -0.58
```

```
## 134                          Paraguay 0.717 40.3    7.54                   0.00
## 135                              Peru 0.762 54.9    7.93                  -0.41
## 136                       Philippines 0.699 45.7    6.83                  -0.93
## 137                            Poland 0.876 55.7    7.96                   0.51
## 138                          Portugal 0.866 54.7    8.69                   0.95
## 139                             Qatar 0.855 48.7    6.15                   0.96
## 140                           Romania 0.821 45.7    8.33                   0.53
## 141                            Russia 0.822 49.1    6.23                  -0.65
## 142                            Rwanda 0.534 33.1    6.36                   0.17
## 143             Saint Kitts and Nevis 0.777 31.7      NA                   0.96
## 144                       Saint Lucia 0.715 34.7      NA                   0.85
## 145 Saint Vincent and the Grenadines 0.751 33.5      NA                   1.04
## 146                             Samoa 0.707 28.8      NA                   1.11
## 147                        San Marino 0.853 32.9      NA                   0.91
## 148             Sao Tome and Principe 0.618 26.6      NA                   0.60
## 149                      Saudi Arabia 0.875 44.9    5.12                  -0.58
## 150                           Senegal 0.511 32.8    7.07                  -0.17
## 151                            Serbia 0.802 45.0    7.54                  -0.13
## 152                        Seychelles 0.785 31.8    7.84                   0.76
## 153                      Sierra Leone 0.477 32.7    6.70                  -0.16
## 154                         Singapore 0.939 57.4    7.98                   1.49
## 155                          Slovakia 0.848 54.4    8.21                   0.56
## 156                          Slovenia 0.918 67.8    8.37                   0.76
## 157                   Solomon Islands 0.564 23.3      NA                   0.49
## 158                      South Africa 0.713 45.8    7.30                  -0.71
## 159                       South Korea 0.925 65.4    8.39                   0.66
## 160                       South Sudan 0.385 21.3      NA                  -2.30
## 161                             Spain 0.905 60.9    8.56                   0.58
## 162                         Sri Lanka 0.782 34.1    6.58                  -0.32
## 163                             Sudan 0.508 28.3    4.48                  -1.94
## 164                          Suriname 0.730 35.0    7.64                   0.37
## 165                            Sweden 0.947 64.9    8.83                   1.03
## 166                       Switzerland 0.962 58.8    9.11                   1.13
## 167                             Syria 0.577 16.7    3.66                  -2.66
## 168                        Tajikistan 0.685 29.3    5.52                  -0.61
## 169                          Tanzania 0.549 31.3    6.48                  -0.44
## 170                          Thailand 0.800 68.2    6.89                  -0.55
## 171                       Timor-Leste 0.607 27.8    7.22                   0.17
## 172                              Togo 0.539 27.8    6.50                  -0.80
## 173                             Tonga 0.745 26.4      NA                   1.07
## 174               Trinidad and Tobago 0.810 36.8    7.70                   0.15
## 175                           Tunisia 0.731 31.5    6.46                  -0.70
## 176                            Turkey 0.838 50.0    5.79                  -1.10
## 177                      Turkmenistan 0.745 31.9      NA                  -0.32
## 178                            Tuvalu 0.641 20.0      NA                   1.28
## 179                            Uganda 0.525 36.5    6.32                  -0.86
## 180                           Ukraine 0.773 38.9    6.86                  -1.10
## 181              United Arab Emirates 0.911 39.6    6.06                   0.65
## 182                    United Kingdom 0.929 67.2    8.75                   0.54
## 183          United States of America 0.921 75.9    8.73                   0.00
## 184                           Uruguay 0.809 40.3    8.36                   1.05
## 185                        Uzbekistan 0.727 39.0      NA                  -0.24
## 186                           Vanuatu 0.607 25.9      NA                   0.79
## 187                         Venezuela 0.691 20.9    4.03                  -1.53
```

```
## 188                          Vietnam 0.703 42.9    5.90               -0.11
## 189                            Yemen 0.455 16.1    4.08               -2.59
## 190                           Zambia 0.565 26.5    6.82                0.06
## 191                         Zimbabwe 0.593 32.4    5.60               -1.03
##      happiness total_vax_per_hundred total_cases_per_mil total_deaths_per_mil
## 1        2.523                 11.37            3843.027              178.853
## 2        5.117                 81.50           73495.999             1130.064
## 3        4.887                 27.94            4855.709              139.656
## 4           NA                146.85          289593.327             1753.441
## 5           NA                 32.64            2157.605               49.369
## 6           NA                129.19           45802.585             1269.036
## 7        5.929                172.04          127015.620             2596.686
## 8        5.283                 58.51          124054.477             2867.139
## 9        7.183                162.66           13850.033               92.790
## 10       7.268                186.55          141452.592             1866.187
## 11       5.171                109.54           59504.476              805.748
## 12          NA                 73.22           59699.163             1748.827
## 13       6.647                219.14          191141.779              946.858
## 14       5.025                 62.26            9262.063              163.985
## 15          NA                106.38          100516.251              923.145
## 16       5.534                 80.84           73162.372              583.222
## 17       6.834                186.45          179883.824             2432.755
## 18          NA                104.77           79122.099             1473.037
## 19       5.045                 13.28            1875.553               12.057
## 20          NA                147.59            3399.548                3.834
## 21       5.716                 80.11           48410.298             1607.478
## 22       5.813                 48.06           89830.928             4152.737
## 23       3.467                 42.89           84421.169              932.213
## 24       6.330                153.86          103401.940             2874.028
## 25          NA                200.09           34454.190              135.857
## 26       5.266                 54.57          109746.821             4554.734
## 27       4.834                  4.65             777.639               14.025
## 28       3.775                  0.06            2370.131                1.086
## 29          NA                 96.29           68679.383              593.430
## 30       4.830                181.64            7185.596              179.629
## 31       5.142                  3.65            3928.633               66.381
## 32       7.103                179.01           54674.470              779.054
## 33          NA                  7.83            2232.240               18.103
## 34       4.355                  1.61             321.667               10.213
## 35       6.172                226.05           92058.065             1994.314
## 36       5.339                198.85              92.420                3.997
## 37       6.012                124.71           99059.263             2503.488
## 38       4.289                 69.50            7785.770              187.623
## 39       5.342                 12.71            3563.730               61.805
## 40       7.069                149.71          110206.152             1419.462
## 41       5.306                 25.26            2419.910               25.284
## 42       5.882                117.35          176082.986             3099.722
## 43          NA                275.36           86117.905              742.227
## 44       6.223                172.00          180555.509              720.977
## 45       6.965                147.62          239885.878             3462.077
## 46          NA                  0.34             800.655               12.372
## 47       7.620                203.62          133231.468              553.529
## 48          NA                  5.77           12162.187              168.622
## 49          NA                 78.40           93652.932              645.977
```

```
## 50      5.545                  125.45          37160.446            378.134
## 51      5.764                  153.14          30320.534           1870.396
## 52      4.283                   47.59           3466.327            195.756
## 53      6.061                  151.83          19212.981            603.340
## 54         NA                   27.03           8185.485            104.483
## 55         NA                      NA           2166.643             20.358
## 56      6.189                  136.41         182347.157           1456.943
## 57      4.308                   33.25          54783.303           1080.987
## 58      4.275                    8.85           3367.185             56.136
## 59         NA                  136.28          57360.484            750.724
## 60      7.842                  173.57          47621.033            307.720
## 61      6.690                  183.22         146728.723           1871.705
## 62      4.852                   16.45          17496.045            120.553
## 63      5.051                   10.89           3758.322            126.756
## 64      4.891                   67.11         249638.058           3685.518
## 65      7.155                  184.68          85942.734           1420.562
## 66      5.088                   23.17           4364.905             39.013
## 67      5.723                  168.22         112691.012           1994.035
## 68         NA                   62.55          48406.252           1594.146
## 69      6.435                   63.39          35119.817            902.380
## 70      4.984                   21.30           2341.236             28.212
## 71         NA                   19.66           3079.437             70.764
## 72         NA                   88.50          48518.227           1299.573
## 73      3.615                    1.70           2258.869             66.724
## 74      5.919                   91.91          36379.485           1000.109
## 75      5.477                  132.54                 NA                 NA
## 76      5.992                  151.24         126053.645           3931.454
## 77      7.554                  192.26          75853.506             96.540
## 78      3.819                  102.24          24583.308            339.465
## 79      5.345                   99.73          15472.592            523.025
## 80      4.721                  131.24          69934.029           1485.840
## 81      4.854                   31.78          47047.604            542.834
## 82      7.085                  196.18         149793.912           1211.999
## 83      7.157                  177.65         146252.196            874.061
## 84      6.483                  188.66         101315.788           2324.744
## 85      6.309                   42.75          33101.647            873.600
## 86      5.940                  162.94          13983.875            148.388
## 87      4.395                   73.24          94060.939           1118.212
## 88      6.152                   90.22          55265.342            939.633
## 89      4.607                   18.51           5409.043             99.505
## 90         NA                   62.61                 NA                 NA
## 91      6.106                  162.63          97597.125            578.137
## 92      5.744                   34.01          27853.952            422.585
## 93      5.030                   77.43          14616.420             47.812
## 94      6.032                  138.09         149500.663           2469.397
## 95      4.584                   79.78         131816.711           1658.001
## 96      3.512                   37.21          12859.600            291.002
## 97      4.625                   16.60           1241.634             54.123
## 98      5.410                   39.34          56982.296            836.129
## 99         NA                  160.12         159827.214           1753.272
## 100     6.255                  150.25         190696.342           2689.761
## 101     7.324                  166.23         158256.396           1412.907
## 102     4.208                    2.51           1697.943             34.682
## 103     3.600                    8.83           3636.356            115.411
```

```
## 104     5.384                 170.46          81162.575               927.038
## 105     5.198                 150.85         182704.019               500.193
## 106     4.723                   4.68            914.861                29.123
## 107     6.602                 201.07          98388.691               894.443
## 108        NA                     NA             96.170                    NA
## 109     4.227                  40.90           8689.344               182.216
## 110     6.049                 156.75          70100.456               604.858
## 111     6.317                 116.71          31644.640              2382.841
## 112        NA                     NA                 NA                    NA
## 113     5.766                  54.28         114812.345              3137.495
## 114     5.677                 157.15         203809.588               584.397
## 115     5.581                 101.19         268446.551              3828.845
## 116     4.918                 134.19          25656.966               396.284
## 117     4.794                  44.64           5587.555                60.541
## 118     4.426                  58.80           9797.725               355.634
## 119     4.574                  24.55          57981.149              1419.932
## 120     5.269                  71.98          27119.361               379.539
## 121     7.464                 162.32         177345.164              1189.079
## 122     7.277                 157.86           2650.961                 9.836
## 123     5.972                 112.04           1951.962                31.230
## 124     5.074                   3.71            281.021                10.455
## 125     4.759                   6.79           1105.114                13.865
## 126     5.101                  83.83         107493.483              3803.963
## 127     7.392                 180.14          72669.388               256.518
## 128        NA                 133.69          66754.583               979.612
## 129     4.934                  66.41           5490.774               122.638
## 130        NA                     NA            552.975                    NA
## 131     4.517                  64.44          89580.227               939.224
## 132     6.180                 140.49         111383.433              1684.215
## 133        NA                   4.97           3564.955                58.170
## 134     5.653                 100.78          68738.907              2451.648
## 135     5.840                 150.06          67181.253              5949.676
## 136     5.880                  93.92          24584.998               444.561
## 137     6.166                 117.89         103098.230              2435.147
## 138     5.929                 194.34         132070.771              1843.760
## 139        NA                 193.15          92680.838               228.931
## 140     6.140                  80.50          91927.269              2986.581
## 141     5.477                 101.14          72557.126              2134.289
## 142     3.415                  91.38           8024.998                97.919
## 143        NA                 115.07          61198.381               587.236
## 144        NA                  58.37          74903.265              1640.055
## 145        NA                  58.87          57253.340               798.392
## 146        NA                 118.35              8.993                    NA
## 147        NA                 160.11         244909.469              2938.557
## 148        NA                  60.52          17049.777               250.667
## 149     6.494                 139.79          15255.011               243.760
## 150     5.132                  10.99           4323.634               109.145
## 151     6.078                 119.91         188770.738              1846.455
## 152        NA                 171.25         231371.634              1176.086
## 153     3.849                  10.09            811.437                14.293
## 154     6.377                 209.25          49505.040               146.709
## 155     6.331                  88.61         149152.071              2947.662
## 156     6.461                 130.29         218941.214              2891.252
## 157        NA                  32.57             33.137                    NA
```

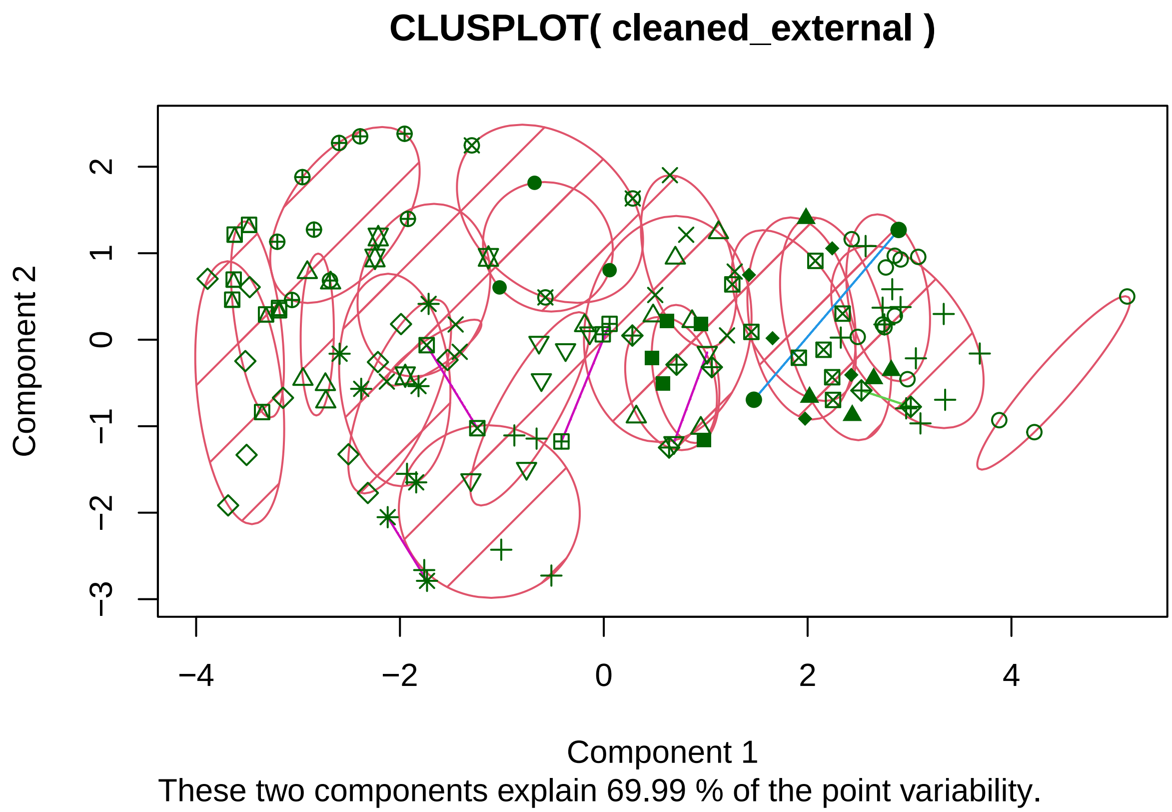
```
## 158     4.956                      46.59              57543.972                 1520.372
## 159     5.845                     200.63              12174.566                  107.361
## 160        NA                       2.46               1431.848                   12.462
## 161     6.491                     175.64             136797.480                 1927.894
## 162     4.325                     155.01              26898.175                  686.098
## 163        NA                       6.99                998.950                   71.191
## 164        NA                      79.25              84186.290                 1923.805
## 165     7.363                     167.00             124623.804                 1453.644
## 166     7.571                     158.42             152718.543                 1363.885
## 167        NA                       7.93               2270.845                  130.756
## 168     5.466                      66.37               1757.598                   12.559
## 169     3.623                       3.71                447.435                   11.252
## 170     5.985                     146.67              31011.538                  302.635
## 171        NA                         NA              14789.405                   90.957
## 172     4.107                      27.28               3408.749                   28.027
## 173        NA                     121.87                  9.357                       NA
## 174        NA                      91.99              59324.918                 1845.147
## 175     4.596                      98.39              58743.540                 2068.935
## 176     4.948                     154.26             110635.410                  962.067
## 177     5.066                       0.80                     NA                       NA
## 178        NA                     106.87                     NA                       NA
## 179     4.636                      20.66               3019.518                   69.778
## 180     4.875                      71.68              92380.048                 2415.486
## 181     6.561                     237.33              80446.976                  228.998
## 182     7.064                     197.47             199109.448                 2220.847
## 183     6.951                     157.08             158249.753                 2421.163
## 184     6.431                     203.91             119875.973                 1802.036
## 185     6.179                     112.73               5744.052                   42.885
## 186        NA                      46.74                 21.423                       NA
## 187     4.892                     106.18              15694.676                  188.010
## 188     5.411                     153.72              17464.069                  327.620
## 189     3.658                       1.62                300.505                   58.878
## 190     4.073                       8.64              12448.652                  186.335
## 191     3.145                      44.51              12973.101                  306.179
```

Clustering indicators, 3(a) - `HDI`: Human Development Index (2021); a value between 0 and 1 that measures average achievement in human development based on three dimensions - life expectancy, education and standard of living. (Source: Human Development Reports) - `GHS`: Global Health Security Index (2021); a value between 0 and 100 that benchmarks a country's health security and preparedness in preventing, detecting and responding to health emergencies. (Source: Global Health Security Index: Reports and Data) - `freedom`: Human Freedom Index (2021); a value between 0 and 10 that assesses the level of human freedom in a country. Human freedom is a combination of two distinct dimensions - personal freedom (freedom of religion, speech, sexual orientation, etc.) and economic freedom (size of government, judicial impartiality, freedom to trade, etc.) (Source: World Population Review) - `political_stability`: a value **approximately** between -2.5 and 2.5 that evaluates political stability and absence of violence/terrorism of each country in 2021. (Source: The World Bank Data Collections (and Governance Indicators)) - `happiness`: World Happiness Report score (2021); a value between 0 and 10 that represents happiness of a country's citizens based on several socioeconomic factors. (Source: World Happiness Report) - `total_vax_per_hundred`: latest updated total number of COVID-19 vaccinations administered per 100 people before 2022. - `total_cases_per_mil`: latest updated total number of COVID-19 cases per 1,000,000 people before 2022. - `total_deaths_per_mil`: latest updated total number of COVID-19 cases per 1,000,000 people before 2022.

The final three indicators being sourced from Our World in Data's COVID-19 Github repository.

K-means clustering, 3(a)

```r
library(cluster)
clusplot(cleaned_external, kfit$cluster, color = TRUE, shade = TRUE, labels = 0, lines = 0)
```



`others` correlation matrix, 3(b)

```r
clustered_correlation_plotted <- ggplot(data = clustered_melted) +
  geom_tile(mapping = aes(x = Var1, y = Var2, fill = value)) +
  scale_fill_gradient2(low = "#6b74ff", mid = "white", high = "#e46c6c", midpoint = 0) +
  labs(title = "Correlation between predictors for countries similar to Croatia",
    x = "", y = "", fill = "correlation") +
  theme(axis.text.x = element_text(angle = 90))
```

`clustered` model, 3(b)

```r
fitted_clus1 <- lm(c19ProSo01 ~ .,
  data = subset(clustered, select = -c(coded_country, c19ProSo02, c19ProSo03, c19ProSo04)))
fitted_clus2 <- lm(c19ProSo02 ~ .,
  data = subset(clustered, select = -c(coded_country, c19ProSo01, c19ProSo03, c19ProSo04)))
fitted_clus3 <- lm(c19ProSo03 ~ .,
  data = subset(clustered, select = -c(coded_country, c19ProSo01, c19ProSo02, c19ProSo04)))
fitted_clus4 <- lm(c19ProSo04 ~ .,
  data = subset(clustered, select = -c(coded_country, c19ProSo01, c19ProSo02, c19ProSo03)))

cat("Model Summary for countries similar to the Croatia to predict pro-social attitudes\n\n")
j <- 1
```

```r
for (model in list(fitted_clus1, fitted_clus2, fitted_clus3, fitted_clus4)) {
  cat("C19ProSo0", j, "\n", sep = "")
  res <- model_evaluated(model)
  cat("R-squared:", res[[1]], "\n")
  cat("Adjusted R-squared:", res[[2]], "\n")
  cat("99.9% confidence interval significant predictors:\n")
  cat(res[[3]], "\n")
  cat("Coefficients of predictors:\n")
  cat(res[[4]], "\n")
  cat("\n")
  j <- j + 1
}
```

`clustered` models, updated `model_evaluated` function with 95% confidence interval, 3(b)

```r
model_evaluated_2 <- function(model) {
  rsqr <- summary(model)$r.squared
  a_rsqr <- summary(model)$adj.r.squared
  sig <- which(summary(model)$coefficients[-1, 4] < 0.05) + 1
  preds <- rownames(summary(model)$coefficients[sig, , drop = FALSE])
  coefs <- summary(model)$coefficients[sig, 1]

  return(list(rsqr, a_rsqr, preds, coefs))
}

cat("Model Summary for countries similar to the Croatia to predict pro-social attitudes\n\n")
counter <- 1
for (model in list(fitted_clus1, fitted_clus2, fitted_clus3, fitted_clus4)) {
  cat("C19ProSo0", counter, "\n", sep = "")
  res <- model_evaluated_2(model)
  cat("R-squared:", res[[1]], "\n")
  cat("Adjusted R-squared:", res[[2]], "\n")
  cat("95% confidence interval significant predictors:\n")
  cat(res[[3]], "\n")
  cat("Coefficients of predictors:\n")
  cat(res[[4]], "\n")
  cat("\n")
  for (each in res[[3]]) {
    each_model <- c(each_model, paste0("Similar_C19ProSo0", counter))
  }
  predictors <- c(predictors, res[[3]])
  counter <- counter + 1
}
```

`croatia`, `others` and `clustered` models strongest predictors, 3(b)

```r
summary_table <- table(predictors = predictors, models = each_model)

summary_table <- summary_table[, c("Croatia_C19ProSo03",
  "Croatia_C19ProSo04", "RoW_C19ProSo01", "RoW_C19ProSo02", "RoW_C19ProSo03", "RoW_C19ProSo04",
 "Similar_C19ProSo01", "Similar_C19ProSo02", "Similar_C19ProSo03", "Similar_C19ProSo04"
  )]
```

```r
summary_table_visualised_2 <- ggplot(data = as.data.frame(summary_table)) +
  geom_tile(mapping = aes(x = models, y = predictors, fill = Freq, colour = "black")) +
  scale_fill_gradientn(colours = c("pink", "green")) +
  theme(legend.position = "none") +
  scale_x_discrete(position = "top") +
  scale_y_discrete(limits = rev) +
  labs(x = "Pro-social attitudes", y = "Predictors",
    title = "Table for each pro-social attitude by significant predictors ") +
  theme(axis.text.x = element_text(angle = 90))
```