European Social Survey: Exploratory data analysis

Data

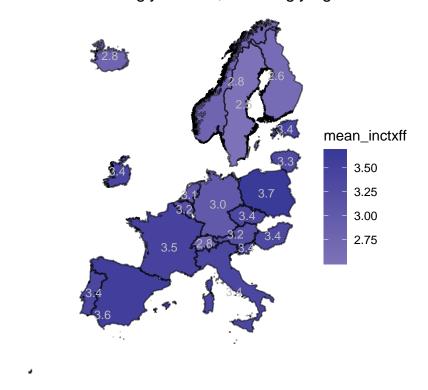
library(tidyverse)
library(essurvey)

gpclibPermit()

```
library(labelled)
library(rstan)
library(rgdal)
library(doBy)
set_email('trubetskoy.vasa@gmail.com')
Round 8 contains questions referring to climate. We can extract these.
round_8 <- import_rounds(8, )</pre>
base_variables <- c('idno', 'cntry')</pre>
interesting_variables <- c('eduyrs')</pre>
questions <- var_label(round_8) %>%
  as_data_frame() %>%
  gather(key = 'variable_name', value = 'description')
## Warning: `as_data_frame()` is deprecated, use `as_tibble()` (but mind the new semantics).
## This warning is displayed once per session.
climate_questions <- questions %>%
  filter(str_detect(description, 'climate'))
responses <- round_8 %>%
  select(one_of(c(base_variables, climate_questions$variable_name, interesting_variables)))
# is this the right thing to do?
responses <- recode_missings(responses, c("Don't know", "Refusal"))</pre>
country_summaries <- responses %>%
  group_by(cntry) %>%
  summarise(mean_inctxff = mean(inctxff, na.rm = T))
Mapping
Starting point: https://gist.github.com/stared/fbca436c885c430a314a
library(maptools)
## Checking rgeos availability: FALSE
##
        Note: when rgeos is not available, polygon geometry
                                                                   computations in maptools depend on gpcl
##
        which has a restricted licence. It is disabled by default;
        to enable gpclib, type gpclibPermit()
```

```
## Warning in gpclibPermit(): support for gpclib will be withdrawn from
## maptools at the next major release
## [1] TRUE
eurMap <- readOGR('../data/NUTS_RG_01M_2016_3035.shp')</pre>
## OGR data source with driver: ESRI Shapefile
## Source: "/Users/vasa/Projects/the_climate_question/data/NUTS_RG_01M_2016_3035.shp", layer: "NUTS_RG_
## with 2016 features
## It has 5 fields
eurMap <- subset(eurMap, nchar(as.character(NUTS_ID)) == 2)</pre>
eurMapDf <- fortify(eurMap, region='NUTS_ID')</pre>
# merge map and data
eurMapDataDf <- merge(eurMapDf, country_summaries, by.x="id", by.y="cntry")</pre>
# sort, so that polygons are drawn correctly
eurMapDataDf <- eurMapDataDf[order(eurMapDataDf$order),]</pre>
# limit data to main Europe
eurMapDataDf <- subset(eurMapDataDf, long > 2e6 & long < 6e6 & lat > 1e6 & lat < 6e6)
# add text; instead of mean I do middle (not to be to biased towards detailed coastlines)
middle = function (x) {
  (\max(x) + \min(x)) / 2
txtVal <- summaryBy(long + lat + mean_inctxff ~ id, data=eurMapDataDf, FUN=middle, keep.names=T)
p <- ggplot(data=eurMapDataDf) +</pre>
  geom_polygon(aes(x=long, y=lat, group=group, fill=mean_inctxff)) +
  geom_path(aes(x=long, y=lat, group=group), color='black', alpha=.5) +
  geom_text(aes(x=long, y=lat, label=sprintf("%.1f", mean_inctxff)), data=txtVal, col="gray", cex=3) +
  scale_fill_gradient2() +
  theme void() +
  coord_equal() +
  ggtitle('"Increasing taxes on fossil fuels, such as oil, gas and coal."\n Scale: 1=strongly in favor
p
```

"Increasing taxes on fossil fuels, such as oil, gas and coal." Scale: 1=strongly in favor, 5=strongly against



Weirdly the UK is missing on this map. ostok119 ## Modeling

Questions

How does income affect climate views?

How does level of education affect climate views?

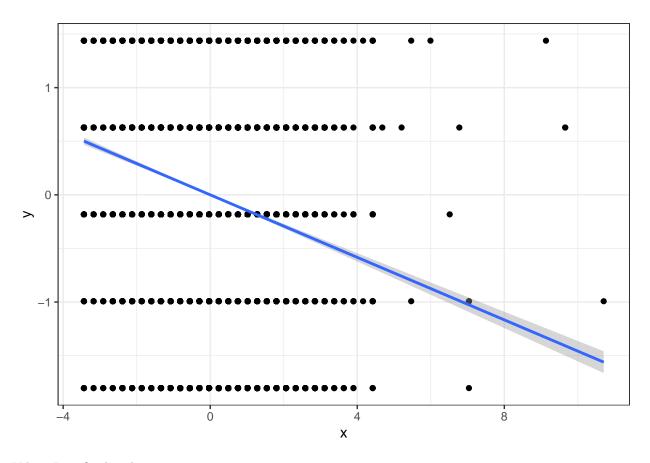
How do climate views differ by country?

Model 01: linear everything

How unrealistic! We can take a look anyway:

```
preprocessed_data <- responses %>%
  select(c(eduyrs, inctxff)) %>%
  drop_na() %>%
  mutate(x = scale(eduyrs) %>% as.vector(), y = scale(inctxff) %>% as.vector())

ggplot(preprocessed_data, aes(x=x, y=y)) +
  geom_point() +
  geom_smooth(method='lm',formula=y~x) +
  theme_bw()
```



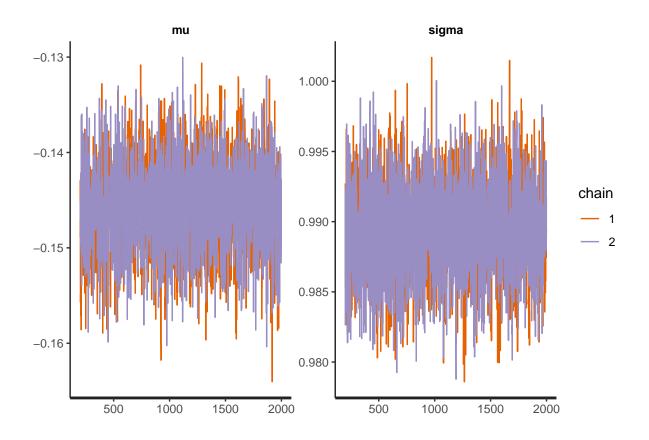
Yikes. Lets fit this thing anyway.

```
stan_data <- preprocessed_data %>%
  select(c(x, y)) %>%
  as.list()
stan_data[['N']] <- length(stan_data[['y']])</pre>
edu_inctxf_fit <-stan(file = '../models/linear_education_climate.stan',</pre>
  data = stan_data,
  iter = 2000,
  warmup = 200,
  chains = 2)
## SAMPLING FOR MODEL 'linear_education_climate' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.006648 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 66.48 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:
                          1 / 2000 [ 0%]
                                            (Warmup)
## Chain 1: Iteration: 200 / 2000 [ 10%]
                                            (Warmup)
## Chain 1: Iteration: 201 / 2000 [ 10%]
                                            (Sampling)
## Chain 1: Iteration: 400 / 2000 [ 20%]
                                            (Sampling)
## Chain 1: Iteration: 600 / 2000 [ 30%]
                                            (Sampling)
```

```
## Chain 1: Iteration: 800 / 2000 [ 40%]
                                            (Sampling)
## Chain 1: Iteration: 1000 / 2000 [ 50%]
                                            (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]
                                            (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]
                                            (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]
                                            (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]
                                            (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]
                                            (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 2.33629 seconds (Warm-up)
## Chain 1:
                           18.6054 seconds (Sampling)
## Chain 1:
                           20.9416 seconds (Total)
## Chain 1:
## SAMPLING FOR MODEL 'linear_education_climate' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0.001788 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 17.88 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:
                          1 / 2000 [ 0%]
                                            (Warmup)
## Chain 2: Iteration: 200 / 2000 [ 10%]
                                            (Warmup)
## Chain 2: Iteration: 201 / 2000 [ 10%]
                                            (Sampling)
## Chain 2: Iteration: 400 / 2000 [ 20%]
                                            (Sampling)
## Chain 2: Iteration: 600 / 2000 [ 30%]
                                            (Sampling)
## Chain 2: Iteration: 800 / 2000 [ 40%]
                                            (Sampling)
## Chain 2: Iteration: 1000 / 2000 [ 50%]
                                            (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]
                                            (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]
                                            (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]
                                            (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]
                                            (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]
                                            (Sampling)
## Chain 2:
## Chain 2:
            Elapsed Time: 2.09905 seconds (Warm-up)
## Chain 2:
                           18.4826 seconds (Sampling)
## Chain 2:
                           20.5817 seconds (Total)
## Chain 2:
```

Look at the trace and parameter estimates.

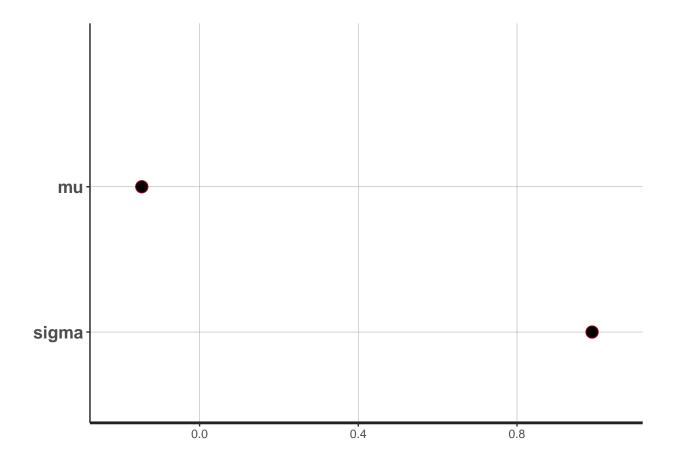
```
traceplot(edu_inctxf_fit)
```



plot(edu_inctxf_fit)

ci_level: 0.8 (80% intervals)

outer_level: 0.95 (95% intervals)



 ${\bf Model~02:~ordinal~response?~ordinal~predictor?}$

Model 03: survey adjustments?

Model 04: hierarchical effects?