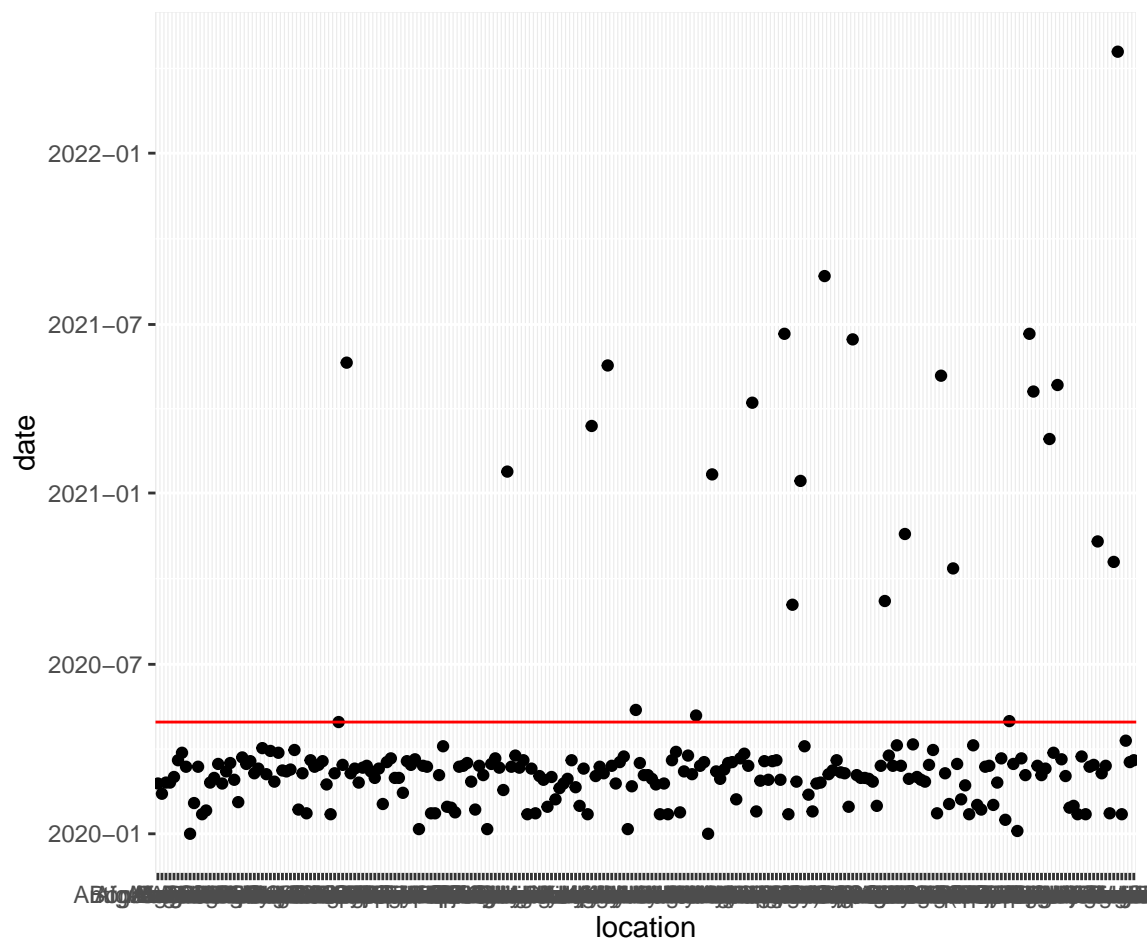


# Cross Section Assignment

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```
## # A tibble: 206 x 1
## # Groups:   location [206]
##   location
```

---

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---

```
##      <chr>
##  1 Afghanistan
##  2 Albania
##  3 Algeria
##  4 Andorra
##  5 Angola
##  6 Anguilla
##  7 Antigua and Barbuda
##  8 Argentina
##  9 Armenia
## 10 Aruba
## # ... with 196 more rows
```

Want to compare the US, with Europe, Africa (excluding SA), and SA (and maybe Asia, or specifically china)

```
## # A tibble: 7 x 1
##   continent
##   <chr>
## 1 Asia
## 2 <NA>
## 3 Europe
## 4 Africa
## 5 North America
## 6 South America
## 7 Oceania
```

[Share of woman vs men](#) in SA about equal

Towards estimating the fixed effects, let's see which variables do not change over the time period we have.

Checking the plots of all the features:

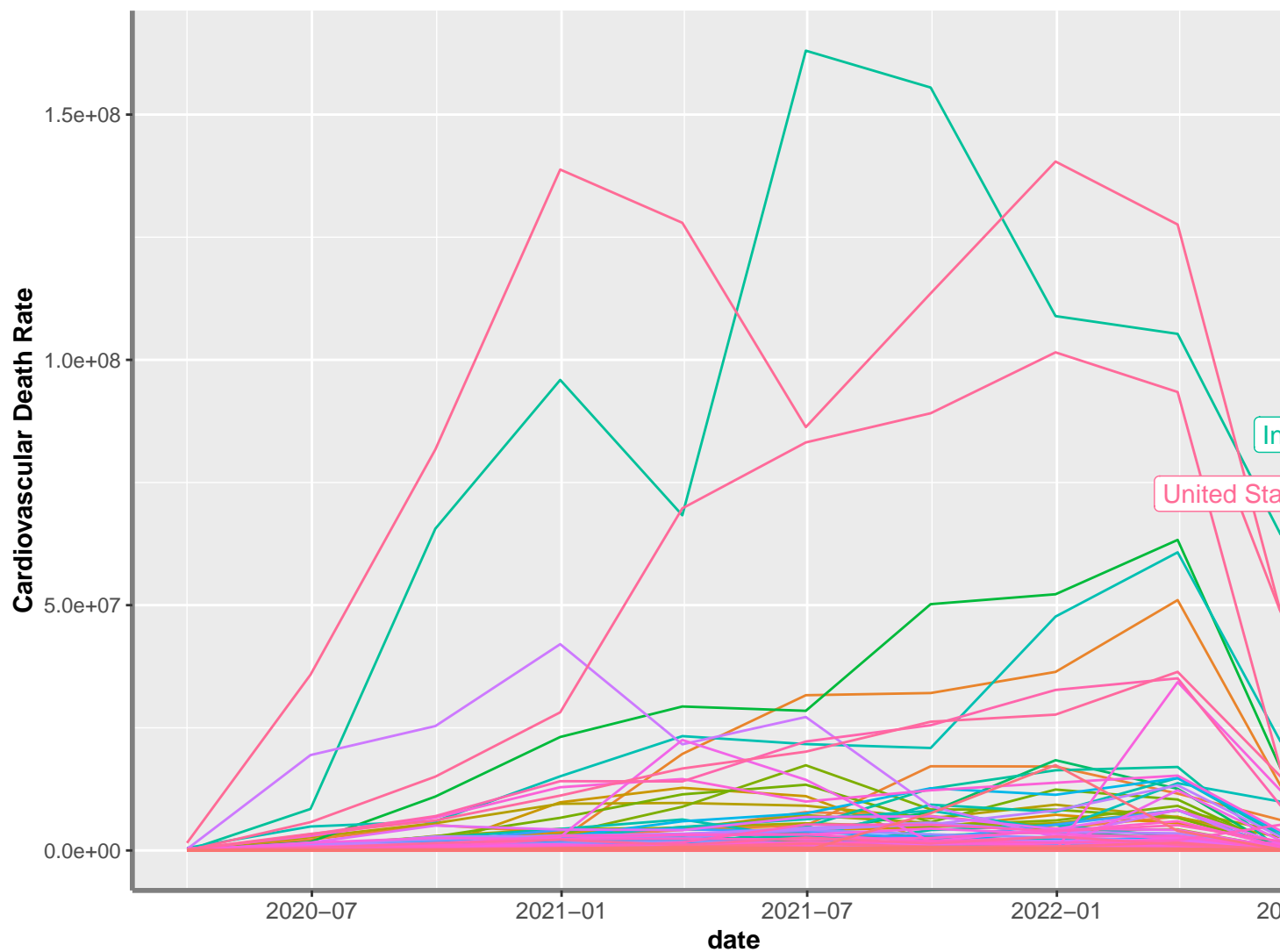
We need to have a look at the correlation between the different variables to see what type of relationships exist. Furthermore, it is important to

##	mean	sd	min	max	range
----	------	----	-----	-----	-------

---

## death_rate	1.88	3.09	0.00	37.50	37.50
## reproduction_rate	0.77	0.44	-0.01	2.06	2.08
## icu_patients	10972.02	83404.37	0.00	1605018.00	1605018.00
## hosp_patients	55286.41	368499.78	0.00	6894400.00	6894400.00
## new_tests	2434948.51	11629111.49	0.00	163020639.00	163020639.00
## new_vaccinations	4859361.59	43022342.39	0.00	1124854000.00	1124854000.00
## stringency_index	44.81	25.15	0.00	99.06	99.06

Plot of Distribution of ICU Patients per day for each Country



Thus, want to scale: `icu_patients`, `hosp_patients`, `new_test`, `new_vaccinations`

Now, to check the scales of the features that remain constant per country:

---

##	mean	sd	min	max	range
## gdp_per_capita	17697.35	20539.28	0	116935.60	116935.60
## population_density	444.44	2094.60	0	20546.77	20546.77
## median_age	27.58	12.79	0	48.20	48.20
## aged_65_older	7.90	6.48	0	27.05	27.05
## extreme_poverty	7.83	16.76	0	77.60	77.60
## cardiovasc_death_rate	226.19	135.19	0	724.42	724.42
## diabetes_prevalence	7.52	4.59	0	23.36	23.36
## handwashing_facilities	21.89	32.72	0	99.00	99.00
## hosp_beds_1k	2.38	2.51	0	13.80	13.80
## life_expectancy	73.36	9.08	0	86.75	86.75
## human_development_index	0.63	0.28	0	0.96	0.96
## smokers	14.38	12.75	0	45.95	45.95

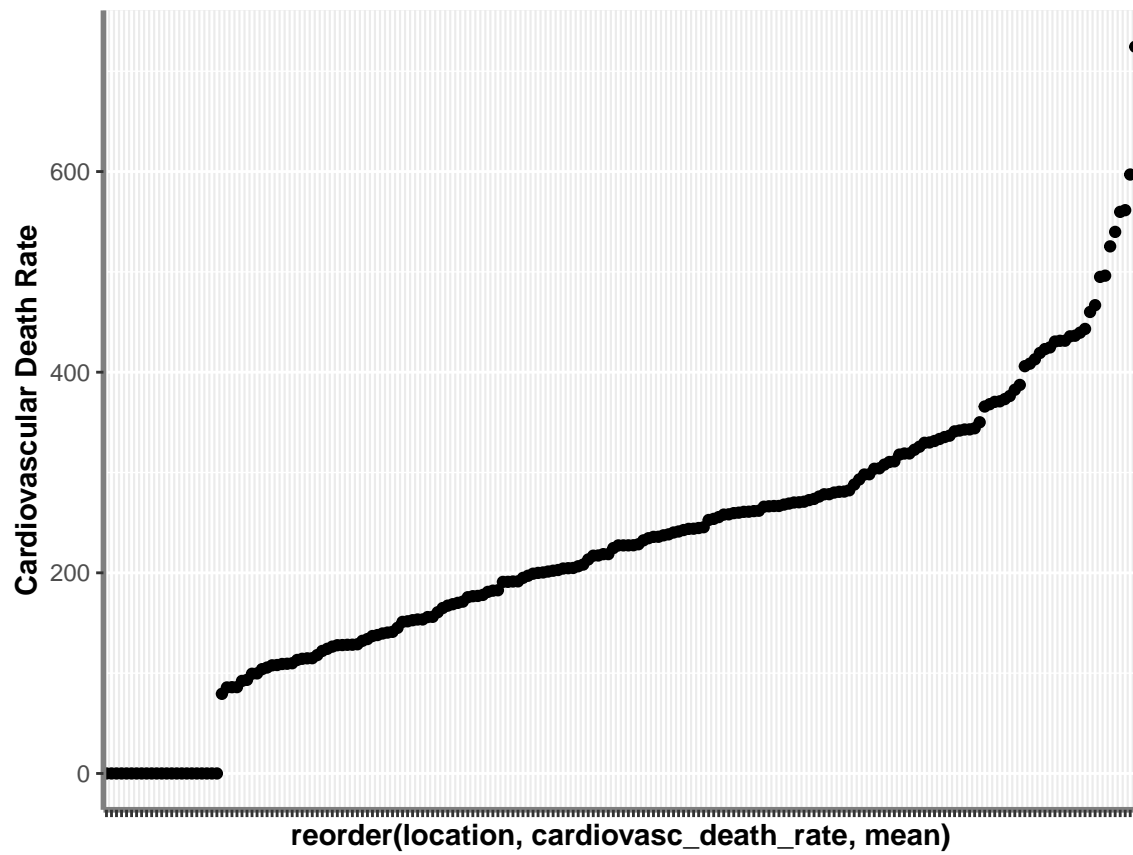
Additional features that need to be scaled are this

- gdp\_per\_capita
- population\_density
- cardiovasc\_death\_rate

---

## Plot of Distribution of Cardiovascular Death Rate per Country

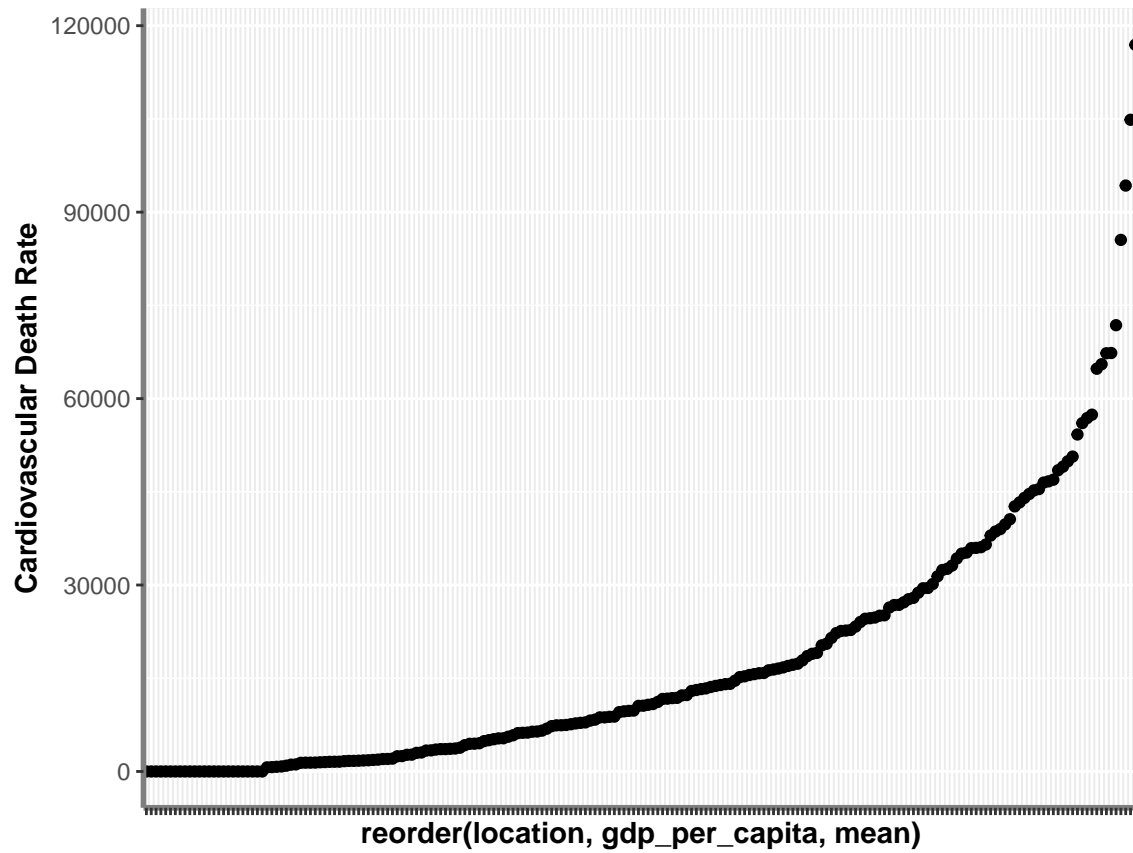
More or less linearly distributed i.e. normalisation scaling



---

## Plot of Distribution of GDP per capita per Country

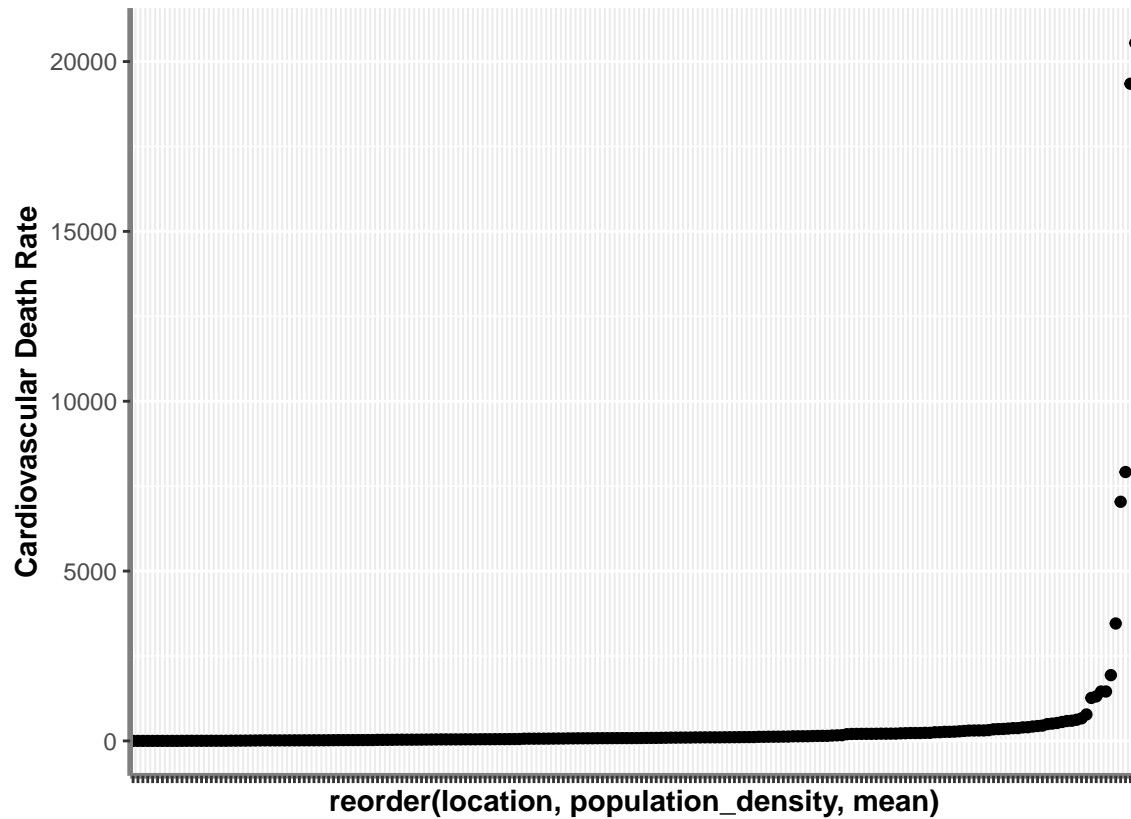
Nonlinear distribution suggests a log transformation



---

## Plot of Distribution of Population Density per Country

Presence of outliers suggests scaling such that outliers remain relatively present, i.e. normalisation



Now we can check all the descriptive stats for all the columns

##	mean	sd	min	max	range
## death_rate	1.88	3.09	0.00	37.50	37.50
## reproduction_rate	0.77	0.44	-0.01	2.06	2.08
## icu_patients	1.79	4.09	0.00	16.01	16.01
## hosp_patients	2.13	4.75	0.00	17.44	17.44
## new_tests	8.07	7.16	0.00	20.62	20.62
## new_vaccinations	6.20	7.11	0.00	21.92	21.92
## stringency_index	44.81	25.15	0.00	99.06	99.06
## population_density	0.00	1.00	-0.21	9.60	9.81
## median_age	27.58	12.79	0.00	48.20	48.20
## aged_65_older	7.90	6.48	0.00	27.05	27.05
## gdp_per_capita	8.21	3.22	0.00	11.67	11.67
## extreme_poverty	7.83	16.76	0.00	77.60	77.60

---

```

## cardiovasc_death_rate    0.00  1.00 -1.67  3.69  5.36
## diabetes_prevalence      7.52  4.59  0.00 23.36 23.36
## handwashing_facilities  21.89 32.72  0.00 99.00 99.00
## hosp_beds_1k             2.38  2.51  0.00 13.80 13.80
## life_expectancy          73.36  9.08  0.00 86.75 86.75
## human_development_index  0.63  0.28  0.00  0.96  0.96
## smokers                  14.38 12.75  0.00 45.95 45.95

## Pooling Model
##
## Call:
## plm(formula = world_df$death_rate ~ world_df$stringency_index +
##      world_df$aged_65_older + world_df$population_density + world_df$gdp_per_capita +
##      world_df$extreme_poverty + world_df$diabetes_prevalence +
##      world_df$smokers + world_df$handwashing_facilities + world_df$life_expectancy +
##      world_df$human_development_index, data = world_df, model = "pooling",
##      index = c("location", "date"))
##
## Unbalanced Panel: n = 206, T = 7-10, N = 2050
##
## Residuals:
##      Min.   1st Qu.   Median   3rd Qu.    Max.
## -3.34154 -1.36040 -0.81011  0.26304 35.51716
##
## Coefficients:
##
##              Estimate Std. Error t-value Pr(>|t|)
## (Intercept)      3.1144564   0.7446268   4.1826 3.004e-05 ***
## world_df$stringency_index      0.0140255   0.0029613   4.7362 2.327e-06 ***
## world_df$aged_65_older      0.0200532   0.0153248   1.3085  0.19084
## world_df$population_density -0.1279423   0.0728308  -1.7567  0.07912 .
## world_df$gdp_per_capita     -0.0263453   0.0330498  -0.7971  0.42546
## world_df$extreme_poverty    -0.0025897   0.0047104  -0.5498  0.58253
## world_df$diabetes_prevalence -0.0197411   0.0160446  -1.2304  0.21869
## world_df$smokers             -0.0082696   0.0070628  -1.1709  0.24179
## world_df$handwashing_facilities  0.0098525   0.0021872   4.5046 7.026e-06 ***
## world_df$life_expectancy     -0.0261921   0.0098585  -2.6568  0.00795 **
## world_df$human_development_index 0.2977904   0.4255525   0.6998  0.48415
## ---

```

---



---

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    19611
## Residual Sum of Squares: 18889
## R-Squared:              0.036848
## Adj. R-Squared: 0.032124
## F-statistic: 7.80073 on 10 and 2039 DF, p-value: 2.2171e-12
```

