

To get an overview we first load the data into R and print the available regions (data for countries and many cities are available) and transportation types ("driving", "transit" and "walking"):

```
mobility <- read.csv("data/applemobilitytrends-2020-04-19.csv") # change path
and file name accordingly
```

```
levels(mobility$region)
```

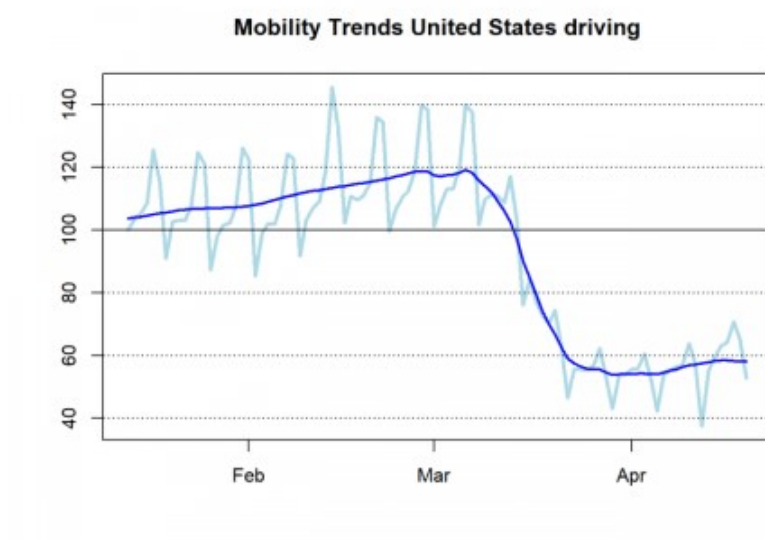
```
##      [1] "Albania"                "Amsterdam"
##      [3] "Argentina"              "Athens"
##      [5] "Atlanta"                "Auckland"
##      [7] "Australia"              "Austria"
##      [9] "Baltimore"              "Bangkok"
##     [11] "Barcelona"              "Belgium"
##     [13] "Berlin"                 "Birmingham - UK"
##     [15] "Bochum - Dortmund"      "Boston"
##     [17] "Brazil"                 "Brisbane"
##     [19] "Brussels"               "Buenos Aires"
##     [21] "Bulgaria"               "Cairo"
##     [23] "Calgary"                "Cambodia"
##     [25] "Canada"                 "Cape Town"
##     [27] "Chicago"                "Chile"
##     [29] "Cologne"                "Colombia"
##     [31] "Copenhagen"             "Croatia"
##     [33] "Czech Republic"         "Dallas"
##     [35] "Delhi"                  "Denmark"
##     [37] "Denver"                 "Detroit"
##     [39] "Dubai"                  "Dublin"
##     [41] "Dusseldorf"             "Edmonton"
##     [43] "Egypt"                  "Estonia"
##     [45] "Finland"                "France"
##     [47] "Frankfurt"              "Fukuoka"
##     [49] "Germany"                "Greece"
##     [51] "Guadalajara"            "Halifax"
##     [53] "Hamburg"                 "Helsinki"
##     [55] "Hong Kong"              "Houston"
##     [57] "Hsin-chu"               "Hungary"
##     [59] "Iceland"                 "India"
##     [61] "Indonesia"              "Ireland"
##     [63] "Israel"                  "Istanbul"
##     [65] "Italy"                   "Jakarta"
##     [67] "Japan"                   "Johannesburg"
##     [69] "Kuala Lumpur"           "Latvia"
##     [71] "Leeds"                   "Lille"
##     [73] "Lithuania"              "London"
##     [75] "Los Angeles"             "Luxembourg"
##     [77] "Lyon"                    "Macao"
##     [79] "Madrid"                  "Malaysia"
##     [81] "Manchester"              "Manila"
##     [83] "Melbourne"               "Mexico"
##     [85] "Mexico City"             "Miami"
##     [87] "Milan"                   "Montreal"
##     [89] "Morocco"                 "Moscow"
##     [91] "Mumbai"                  "Munich"
##     [93] "Nagoya"                  "Netherlands"
##     [95] "New York City"           "New Zealand"
##     [97] "Norway"                  "Osaka"
##     [99] "Oslo"                    "Ottawa"
```

```
## [101] "Paris" "Perth"
## [103] "Philadelphia" "Philippines"
## [105] "Poland" "Portugal"
## [107] "Republic of Korea" "Rio de Janeiro"
## [109] "Riyadh" "Romania"
## [111] "Rome" "Rotterdam"
## [113] "Russia" "Saint Petersburg"
## [115] "San Francisco - Bay Area" "Santiago"
## [117] "Sao Paulo" "Saudi Arabia"
## [119] "Seattle" "Seoul"
## [121] "Serbia" "Singapore"
## [123] "Slovakia" "Slovenia"
## [125] "South Africa" "Spain"
## [127] "Stockholm" "Stuttgart"
## [129] "Sweden" "Switzerland"
## [131] "Sydney" "Taichung"
## [133] "Taipei" "Taiwan"
## [135] "Tel Aviv" "Thailand"
## [137] "Tijuana" "Tokyo"
## [139] "Toronto" "Toulouse"
## [141] "Turkey" "UK"
## [143] "Ukraine" "United Arab Emirates"
## [145] "United States" "Uruguay"
## [147] "Utrecht" "Vancouver"
## [149] "Vienna" "Vietnam"
## [151] "Washington DC" "Zurich"
```

```
levels(mobility$transportation_type)
## [1] "driving" "transit" "walking"
```

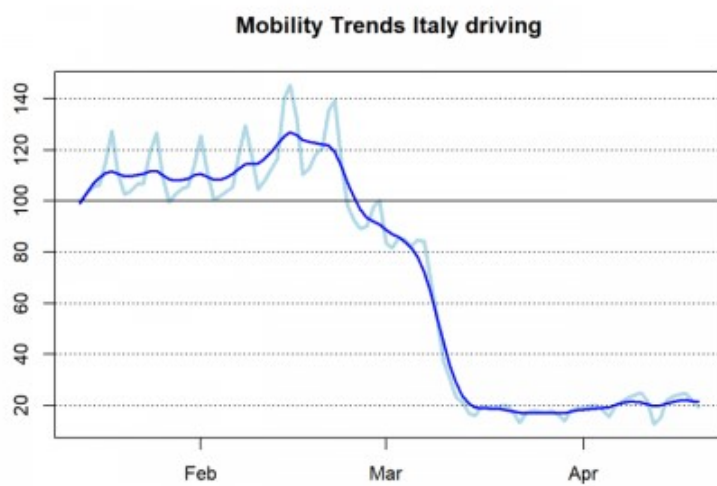
We now create a function `mobi_trends` to return the data in a well-structured format. The default `plot = TRUE` plots the data, `plot = FALSE` returns a named vector with the raw data for further investigation:

```
mobi_trends <- function(reg = "United States", trans = "driving", plot = TRUE,
  addsmooth = TRUE) {
  data <- subset(mobility, region == reg & transportation_type == trans)
  [4:ncol(mobility)]
  dates <- as.Date(sapply(names(data), function(x) substr(x, start = 2, stop =
11)), "%Y.%m.%d")
  values <- as.numeric(data)
  series <- setNames(values, dates)
  if (plot) {
    plot(dates, values, main = paste("Mobility Trends", reg, trans), xlab = "",
ylab = "", type = "l", col = "blue", lwd = 3)
    if (addsmooth) {
      lines(dates, values, col = "lightblue", lwd = 3)
      lines(supsmu(dates, values), col = "blue", lwd = 2)
    }
    abline(h = 100)
    abline(h = c(0, 20, 40, 60, 80, 120, 140, 160, 180, 200), lty = 3)
    invisible(series)
  } else series
}
mobi_trends()
```



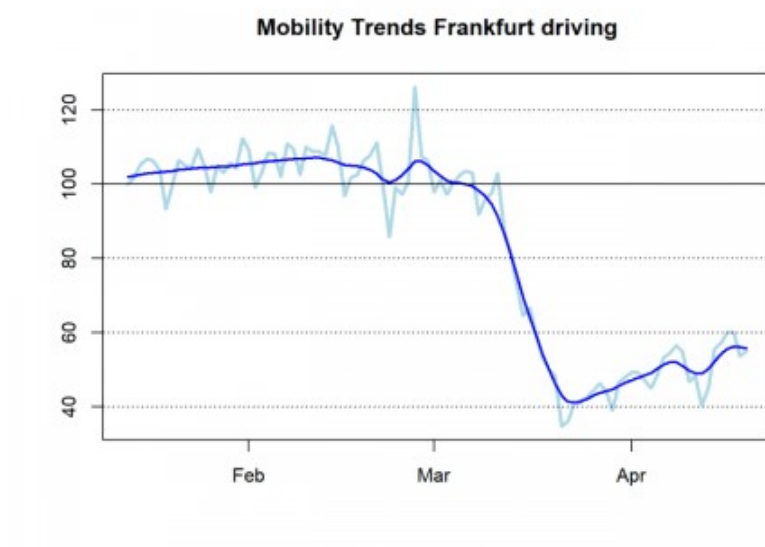
The drop is quite dramatic... by 60%! Even more dramatic, of course, is the situation in Italy:

```
mobi_trends(reg = "Italy")
```



A drop by 80%! The same plot for Frankfurt:

```
mobi_trends(reg = "Frankfurt")
```



Obviously in Germany people are taking those measures less seriously lately, there seems to be a clear upward trend. This can also be seen in the German “walking” data:

```
mobi_trends(reg = "Germany", trans = "walking")
```



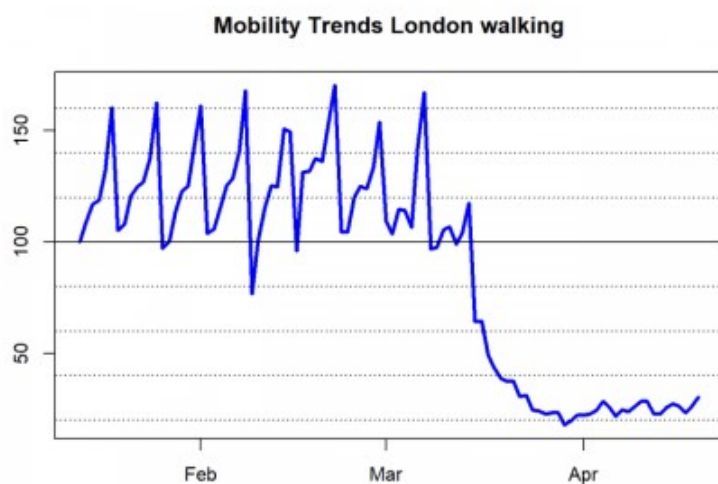
What is interesting is that before the lockdown “transit” mobility seems to have accelerated before plunging:

```
mobi_trends(reg = "Germany", trans = "transit")
```



You can also plot the raw numbers only, without an added smoother (option `addsmooth = FALSE`):

```
mobi_trends(reg = "London", trans = "walking", addsmooth = FALSE)
```



And as I said, you can conduct your own analyses on the formatted vector of the time series (option `plot = FALSE`)...

```
mobi_trends(reg = "London", trans = "walking", plot = FALSE)
## 2020-01-13 2020-01-14 2020-01-15 2020-01-16 2020-01-17 2020-01-18
##      100.00      108.89      116.84      118.82      132.18      160.29
## 2020-01-19 2020-01-20 2020-01-21 2020-01-22 2020-01-23 2020-01-24
##      105.12      108.02      120.52      124.81      127.01      137.38
## 2020-01-25 2020-01-26 2020-01-27 2020-01-28 2020-01-29 2020-01-30
##      162.41       97.16      100.01      113.27      122.75      124.96
## 2020-01-31 2020-02-01 2020-02-02 2020-02-03 2020-02-04 2020-02-05
##      144.13      161.17      103.93      105.67      115.03      125.42
## 2020-02-06 2020-02-07 2020-02-08 2020-02-09 2020-02-10 2020-02-11
##      128.43      140.65      167.80       76.79      100.51      115.26
## 2020-02-12 2020-02-13 2020-02-14 2020-02-15 2020-02-16 2020-02-17
##      125.35      124.69      150.77      149.35       96.03      131.20
## 2020-02-18 2020-02-19 2020-02-20 2020-02-21 2020-02-22 2020-02-23
##      131.72      137.59      136.05      153.95      170.22      104.41
## 2020-02-24 2020-02-25 2020-02-26 2020-02-27 2020-02-28 2020-02-29
```

##	104.32	119.88	125.12	123.88	133.76	153.92
##	2020-03-01	2020-03-02	2020-03-03	2020-03-04	2020-03-05	2020-03-06
##	109.26	103.64	114.68	114.25	106.50	142.09
##	2020-03-07	2020-03-08	2020-03-09	2020-03-10	2020-03-11	2020-03-12
##	167.10	96.86	97.50	105.54	106.91	98.87
##	2020-03-13	2020-03-14	2020-03-15	2020-03-16	2020-03-17	2020-03-18
##	104.19	117.44	64.28	64.53	48.95	43.31
##	2020-03-19	2020-03-20	2020-03-21	2020-03-22	2020-03-23	2020-03-24
##	38.76	37.49	37.36	30.76	31.25	24.63
##	2020-03-25	2020-03-26	2020-03-27	2020-03-28	2020-03-29	2020-03-30
##	24.09	22.89	23.40	23.40	17.83	19.72
##	2020-03-31	2020-04-01	2020-04-02	2020-04-03	2020-04-04	2020-04-05
##	22.29	22.19	22.76	24.34	28.49	26.06
##	2020-04-06	2020-04-07	2020-04-08	2020-04-09	2020-04-10	2020-04-11
##	21.63	24.64	23.87	26.13	28.59	28.58
##	2020-04-12	2020-04-13	2020-04-14	2020-04-15	2020-04-16	2020-04-17
##	22.86	22.80	25.66	27.44	26.40	23.27
##	2020-04-18	2020-04-19				
##	26.36	30.40				

...as we have only scratched the surface of the many possibilities here, there are many interesting analyses, like including the data in epidemiological models or simply calculate correlations with new infections/deaths: please share your findings in the comments below!
