COVID 19 US Total Case and Death Estimates & Forecasts

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1 Install latest NNS (0.5.1)

```
# Install NNS >= 0.5.1, uncomment next line if NNS >= 5.1 not installed already
# library(devtools); install_github('OVVO-Financial/NNS', ref = "NNS-Beta-Version")
library(NNS)
library(data.table)
library(xtable)
```

2 Read and convert data

NY Times covid 19 data repository: `https://github.com/nytimes/covid-19-data`

```
data <- read.csv("https://raw.githubusercontent.com/nytimes/covid-19-data/master/us-states.csv",
                 header = TRUE, sep = ",")
data <- data.table(data)
totals <- data[, lapply(.SD, sum), .SDcols = c("cases","deaths"), by = date]
```

3 Create growth rate for total cases

In this step, we are doing a univariate time-series estimation of the observed growth rate in **total cases**. We use **NNS.ARMA** on cross-validated parameters via the **NNS.ARMA.optim** function.

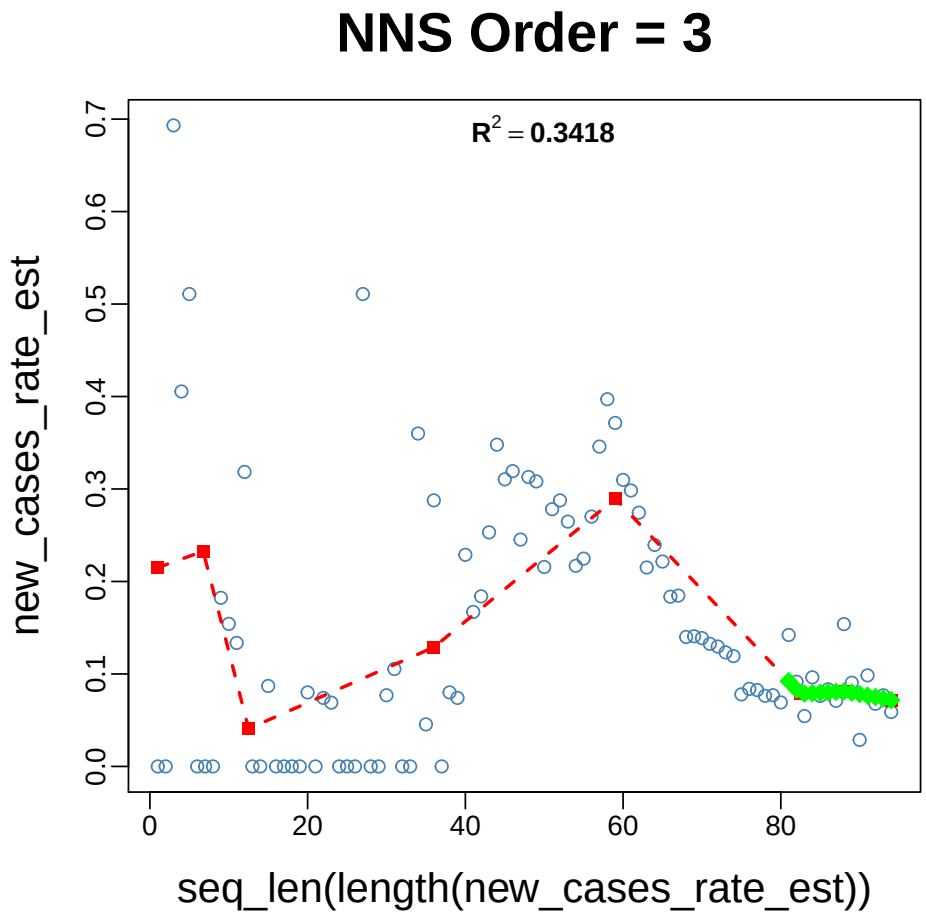
```
new_cases_rate <- log(totals$cases/shift(totals$cases,1))
new_cases_rate <- new_cases_rate[-1]
l <- length(new_cases_rate)
a <- NNS.seas(new_cases_rate, modulo = 7)
b <- NNS.ARMA.optim(new_cases_rate, training.set = l-14, seasonal.factor = a$periods,
                    print.trace = FALSE)
new_cases_rate_est <- NNS.ARMA(new_cases_rate, h = 14, seasonal.factor = b$periods,
                               weights = b$weights) + b$bias.shift
```

3.1 Smooth growth rate point estimates and generate CI

With this new **extended growth rate** time series, we smooth the point estimates provided and generate a 0.95 confidence interval using $\pm 2\sigma$ of the observed growth rates. The image below is the regression of the **extended growth rate**. 0 is the critical point to achieve.

```
new_cases_rate_est_raw <- c(new_cases_rate, new_cases_rate_est)
new_cases_rate_est <- c(new_cases_rate, new_cases_rate_est)
new_cases_rate_est <- NNS.reg(seq_len(length(new_cases_rate_est)), new_cases_rate_est,
```

```
                                point.est = tail(1:length(new_cases_rate_est),14))$Point.est
new_cases_rate_est <- new_cases_rate_est + 1
# Lower CI Case rate
new_cases_rate_est_lower <- pmax(0, new_cases_rate_est_raw - 2 * sd(new_cases_rate_est_raw))
new_cases_rate_est_lower <- c(new_cases_rate, new_cases_rate_est_lower)
new_cases_rate_est_lower <- NNS.reg(seq_len(length(new_cases_rate_est_lower)),
                                    new_cases_rate_est_lower,
                                point.est = tail(1:length(new_cases_rate_est_lower), 14),
                                plot = FALSE)$Point.est
new_cases_rate_est_lower <- new_cases_rate_est_lower + 1
# Upper CI Case rate
new_cases_rate_est_upper <- new_cases_rate_est_raw + 2 * sd(new_cases_rate_est_raw)
new_cases_rate_est_upper <- c(new_cases_rate, new_cases_rate_est_upper)
new_cases_rate_est_upper <- NNS.reg(seq_len(length(new_cases_rate_est_upper)),
                                    new_cases_rate_est_upper,
                                point.est = tail(1:length(new_cases_rate_est_upper), 14),
                                plot = FALSE)$Point.est
new_cases_rate_est_upper <- new_cases_rate_est_upper + 1
```



4 Apply growth rates to estimate total cases

Using the growth rates from the above step, we can now apply them to the last known value of **total cases** and extrapolate. We do this for the **lower growth rate** as well as the **upper growth rate**.

```
cases_est <- numeric()
for(i in 1:length(new_cases_rate_est)){
  if(i >1){
    cases_est[i] <- cases_est[i-1]*new_cases_rate_est[i]
    } else {
    cases_est[i] <- tail(totals$cases,1)*new_cases_rate_est[i]
    }
}
lower_cases_est <- numeric()
for(i in 1:length(new_cases_rate_est_lower)){
  if(i >1){
    lower_cases_est[i] <- lower_cases_est[i-1]*new_cases_rate_est_lower[i]
    } else {
    lower_cases_est[i] <- tail(totals$cases,1)*new_cases_rate_est_lower[i]
    }
}
upper_cases_est <- numeric()
for(i in 1:length(new_cases_rate_est_upper)){
  if(i >1){
    upper_cases_est[i] <- cases_est[i-1]*new_cases_rate_est_upper[i]
    } else {
    upper_cases_est[i] <- tail(totals$cases,1)*new_cases_rate_est_upper[i]
    }
}
```

5 Assign death rate and CI

We will use the last observed **death rate**, and apply $\pm 2\sigma$ from the observed death rates to determine a **lower death rate** and an **upper death rate**.

```
death_rate <- totals$deaths/totals$cases
death_rate <- death_rate[-1]
death_rate_est <- tail(death_rate,1)
lower_death_rate_est <- max(0, death_rate_est - 2*sd(death_rate))
upper_death_rate_est <- death_rate_est + 2*sd(death_rate)
```

6 Estimate total deaths from estimated total cases

Using the death rates from the above step, we can now apply them to the estimated total cases in section 4, creating a lower and upper interval for **estimated total deaths**.

```
new_deaths <- c(totals$deaths,death_rate_est*cases_est)
forecast_points <- tail(1:length(new_deaths), 14)
deaths_est <- NNS.reg(seq_len(length(new_deaths)), new_deaths,
                      point.est = forecast_points)$Point.est
new_deaths_lower <- c(totals$deaths,lower_death_rate_est*cases_est)
lower_deaths_est <- NNS.reg(seq_len(length(new_deaths_lower)), new_deaths_lower,
                            point.est = forecast_points)$Point.est
lower_deaths_est <- pmax(lower_deaths_est, tail(totals$deaths,1))
new_deaths_upper <- c(totals$deaths,upper_death_rate_est*cases_est)
upper_deaths_est <- NNS.reg(seq_len(length(new_deaths_upper)), new_deaths_upper,
                            point.est = forecast_points)$Point.est
date <- seq(as.Date(tail(totals$date,1)), by = "day", length.out = 15)[-1]
estimates <- cbind.data.frame(as.character(date),
                              cases_est, lower_cases_est, upper_cases_est,
                              deaths_est, lower_deaths_est, upper_deaths_est)
colnames(estimates)[1] <- "date"
```

7 Results

7.1 Last known values:

	date	cases	deaths
1	2020-04-05	336774	9655
2	2020-04-06	366238	10959
3	2020-04-07	397754	12956
4	2020-04-08	429319	14803
5	2020-04-09	463684	16674
6	2020-04-10	496912	18742

7.2 Estimates:

	date	cases_est	lower_cases_est	upper_cases_est	deaths_est	lower_deaths_est	upper_deaths_est
1	2020-04-11	542712	500734	685135	20338	18742	34024
2	2020-04-12	587859	504290	743319	22322	18742	38717
3	2020-04-13	634174	507572	799776	24306	18742	43410
4	2020-04-14	684416	510576	859679	26290	18742	48103
5	2020-04-15	738940	513295	927485	28274	18742	52796
6	2020-04-16	798132	515725	1001046	30258	18742	57490
7	2020-04-17	862417	517861	1080882	32241	18742	62183
8	2020-04-18	932258	519699	1167560	34225	18742	66876
9	2020-04-19	1006717	521237	1261702	37008	18742	72749
10	2020-04-20	1085461	522470	1362029	40615	18742	79839
11	2020-04-21	1168570	523398	1468085	44221	18742	86928
12	2020-04-22	1256113	524017	1579975	47624	18742	93618
13	2020-04-23	1348139	524327	1697783	50958	18742	100172
14	2020-04-24	1444681	524327	1821573	54292	18742	106726

7.3 Yesterday's Forecasted and Actual Values:

To compare yesterday's forecasted versus the actual reported values (*plus any revisions to existing data*), we can repeat all of the previous steps on the modified dataset by removing the last entry and creating the object **yesterday**.

```
yesterday <- totals[-.N,]
print(xtable(tail(yesterday)))
```

	date	cases	deaths
1	2020-04-04	311536	8499
2	2020-04-05	336774	9655
3	2020-04-06	366238	10959
4	2020-04-07	397754	12956
5	2020-04-08	429319	14803
6	2020-04-09	463684	16674

```
yesterday_new_cases_rate <- log(yesterday$cases/shift(yesterday$cases,1))
yesterday_new_cases_rate <- yesterday_new_cases_rate[-1]
l <- length(yesterday_new_cases_rate)
a <- NNS.seas(yesterday_new_cases_rate, modulo = 7)
b <- NNS.ARMA.optim(yesterday_new_cases_rate, training.set = l-14, seasonal.factor = a$periods,
```

```
                    print.trace = FALSE)
yesterday_new_cases_rate_est <- NNS.ARMA(yesterday_new_cases_rate, h = 14,
                                         seasonal.factor = b$periods,
                                  weights = b$weights) + b$bias.shift
yesterday_new_cases_rate_est <- c(new_cases_rate, yesterday_new_cases_rate_est)
yesterday_new_cases_rate_est <- NNS.reg(seq_len(length(yesterday_new_cases_rate_est)),
                                        yesterday_new_cases_rate_est,
                           point.est = tail(1:length(yesterday_new_cases_rate_est),14))$Point.est
yesterday_new_cases_rate_est <- yesterday_new_cases_rate_est + 1
yesterday_cases_est <- numeric()
for(i in 1:length(yesterday_new_cases_rate_est)){
  if(i >1){
    yesterday_cases_est[i] <- yesterday_cases_est[i-1]*yesterday_new_cases_rate_est[i]
    } else {
    yesterday_cases_est[i] <- tail(yesterday$cases,1)*yesterday_new_cases_rate_est[i]
    }
}
yesterday_death_rate <- yesterday$deaths/yesterday$cases
yesterday_death_rate <- yesterday_death_rate[-1]
yesterday_death_rate_est <- tail(yesterday_death_rate,1)
yesterday_new_deaths <- c(yesterday$deaths, yesterday_death_rate_est*yesterday_cases_est)
yesterday_forecast_points <- tail(1:length(yesterday_new_deaths), 14)
yesterday_deaths_est <- NNS.reg(seq_len(length(yesterday_new_deaths)), yesterday_new_deaths,
                       point.est = yesterday_forecast_points)$Point.est
yesterday_date <- seq(as.Date(tail(yesterday$date,1)), by = "day", length.out = 15)[-1]
yesterday_estimates <- cbind.data.frame(as.character(yesterday_date),
                                yesterday_cases_est,
                                yesterday_deaths_est)
colnames(yesterday_estimates)[1] <- "date"
```

7.3.1 Yesterday's Forecast:

```
head(yesterday_estimates, 1)
```

```
        date yesterday_cases_est yesterday_deaths_est
1 2020-04-10            510568.8             18698.58
```

7.3.2 Yesterday's Actual:

```
tail(totals,1)
```

```
         date  cases deaths
1: 2020-04-10 496912  18742
```

7.3.3 Yesterday's Forecast Percentage Error:

Yesterday NNS Total Cases Percentage Error:	2.7483%
Yesterday NNS Total Deaths Percentage Error:	-0.2316%

7.3.4 Baseline nls Estimate:

We will use the nls function in R to estimate a nonlinear model and compare to **NNS** on yesterday's values. We will use the following nonlinear parametric form:

$$y = \alpha e^{\beta x} + \theta$$

```
theta.0 <- min(yesterday$cases) * 0.5
# Estimate the rest parameters using a linear model
model.0 <- lm(log(yesterday$cases - theta.0) ~ seq_len(length(yesterday$cases)))
alpha.0 <- exp(coef(model.0)[1])
beta.0 <- coef(model.0)[2]
# Starting parameters
start <- list(alpha = alpha.0, beta = beta.0, theta = theta.0)
model <- nls(yesterday$cases ~ alpha * exp(beta * seq_len(length(yesterday$cases))) + theta ,
             data = yesterday, start = start)
coef(model)
```

```
      alpha          beta         theta
 40.7026242     0.1180111 -5857.3871514
```

Now forecast the nls model for the next period's **total cases** and apply the same **death rate** estimate used in the **NNS** model.

```
nls_cases_forecast <- coef(model)[1]*exp(coef(model)[2]*(length(yesterday$cases)+1)) + coef(model)[3]
as.numeric(nls_cases_forecast)
```

```
[1] 570906.7
```

```
nls_deaths_forecast <- nls_cases_forecast * yesterday_death_rate_est
as.numeric(nls_deaths_forecast)
```

```
[1] 20529.71
```

Yesterday nls Total Cases Percentage Error:	14.8909%
Yesterday nls Total Deaths Percentage Error:	9.5385%