

# Climate Change Calculated, Corona Update

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## Climate Change:

- We had an **record warm winter**, with almost no snow or frost:  
<https://www.theguardian.com/environment/2020/mar/05/truly-extreme-winter-2019-20-in-europe-by-far-hottest-on-record>
- During the Corona restrictions, the air becomes **noticeably more clear**. Less pollution, less CO<sub>2</sub> in the air, more sunshine:  
<https://www.nbcnews.com/science/environment/corona-virus-shutdowns-have-unintended-climate-benefits-n1161921>
- <https://earthobservatory.nasa.gov/images/146362/airborne-nitrogen-dioxide-plummets-over-china>

- This shows the short term **effect of air pollution** (and the removal of it)

## An Update on the Corona Virus:

- **Despite the start of spring**, the new Corona virus **continues** to spread all over the world, unlike a common flu. That is bad.
- There are questions **how it compares to the common flu**

### Comparison: A few virological or epidemiology parameters:

- **Basic Reproduction Number R0:**  
[https://en.wikipedia.org/wiki/Basic\\_reproduction\\_number](https://en.wikipedia.org/wiki/Basic_reproduction_number)  
 It is the average number of persons that an infected person infects. This is what we can influence, e.g. with social distancing.
- **Serial interval:**  
[https://en.wikipedia.org/wiki/Serial\\_interval](https://en.wikipedia.org/wiki/Serial_interval)  
 The time over which these infections appear.
- From R0 and the serial interval t in days we can **compute our daily factor of increase f** for our model:  

$$R0 = f^t$$

$$R0^{(1/t)} = f$$

### Corona, Sars-Cov2:

- [https://www.rki.de/DE/Content/InfAZ/N/Neuartiges\\_Coronavirus/Steckbrief.html?sessionid=0F0255B86EEC44](https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Steckbrief.html?sessionid=0F0255B86EEC44)

[40DA2C6E122ADA9FCF.internet061#doc13776792bodyText3](https://www.who.int/publications-detail/40DA2C6E122ADA9FCF.internet061#doc13776792bodyText3)

- **R0**: 2-3.3 (average number of infected), let's assume ca. **2.7**
- **Serial interval**: 4-7.5 Days (time over which the infections occur), let's assume ca. **5.7**.
- Hence: **Daily factor of increase**:  $f=2.7^{1/5.7}=1.19$
- Sars-Cov2 mortality rate:
- <https://www.ecdc.europa.eu/en/2019-ncov-background-disease>
- <https://time.com/5798168/coronavirus-mortality-rate/>
- [https://www.paho.org/hq/index.php?option=com\\_content&view=article&id=15760:similarities-and-differences-covid-19-and-influenza&catid=740&lang=en&Itemid=1926](https://www.paho.org/hq/index.php?option=com_content&view=article&id=15760:similarities-and-differences-covid-19-and-influenza&catid=740&lang=en&Itemid=1926)

They give a range of about 0.6% to 5%

For my model for the long term prediction I assume a **2% mortality rate**.

Example of a country with good testing, isolating infected, and good hospitals, and where the case numbers stabilized:

**South Korea**: April 1: 165 death, cases 16 days ago (March 15) (assumption from last part): 8200 cases, hence mortality rate:  $165/8200=0.02$ , or 2%. Indeed quite close to my 2% assumption.

## Seasonal Influenza:

- **Basic reproduction number**:  
[https://en.wikipedia.org/wiki/Basic\\_reproduction\\_number](https://en.wikipedia.org/wiki/Basic_reproduction_number)

Seasonal Influenza:  $R_0=0.9-2.1$ , let's assume ca. **1.5**

- **Serial interval** ca. **3 days**.
- Hence: **Daily factor of increase**:  $f=1.5^{(1 / 3)}=1.14$
- **Fatality rate**: ca. **0.1%**

<https://en.wikipedia.org/wiki/Influenza>

[https://www.paho.org/hq/index.php?option=com\\_content&view=article&id=15760:similarities-and-differences-covid-19-and-influenza&catid=740&lang=en&Itemid=1926](https://www.paho.org/hq/index.php?option=com_content&view=article&id=15760:similarities-and-differences-covid-19-and-influenza&catid=740&lang=en&Itemid=1926)

## Spanish Flu:

- [https://en.wikipedia.org/wiki/Basic\\_reproduction\\_number](https://en.wikipedia.org/wiki/Basic_reproduction_number)

1918 pandemic strain:

$R_0=1.4-2.8$ , let's assume ca. **2.0**

- <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0049482>:

**Serial interval: 4 days**

- Hence: **Daily factor of increase**:  $f=2.0^{(1 / 4)}=1.19$
- Fatality or mortality rates:

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3291398/>

<https://www.nytimes.com/2020/04/02/nyregion/spanish-flu-nyc-virus.html>

The 1918 Spanish influenza pandemics “Case-fatality rates were  $>2.5\%$ , compared to  $<0.1\%$  in other influenza pandemics”.

**Table:  $R_0$ , serial interval, daily rate of increase of seasonal flu, Sars-Cov2, Spanish Flu**

	R0	Serial Interval	Daily fact. of incr. f	Mortality rate
Spanish Flu	Ca. 2.0	Ca. 4 days	1.19	>2.5%
Seasonal Flu	Ca. 1.5	Ca. 3	1.14	<0.1%
Sars-Cov2	Ca. 2.7	Ca. 5.7	1.19	Ca. 2%

Observe:

- the **new Corona virus Sars-Cov2 and the Spanish Flu** have **similar** daily factors of increase and mortality rate.
- The **seasonal flu** has a **significantly lower mortality rate**.

The Spanish Flu only spread from people with symptoms. Sars-Cov2 spreads from people **before they show symptoms**. That is bad. That makes it significantly easier to spread, and makes Corona tests essential.

Further **important difference**: for the seasonal flu there are **vaccines** and a good portion of the population has immunity, which limits the number of **susceptible people** and the spread, which is good

For Sars-Cov2 **everybody** is susceptible, which is bad. This is also similar to the Spanish Flu, or the Native Americans after the arrival of Europeans, who mostly died of the flu or cold, because they had **no immunity**.

# Review and update of my model with data from March.

The Johns-Hopkins University maintains a practical **GitHub repository** with their data. I use **Python Pandas** to read in the data to compare it with my model, with the commands,

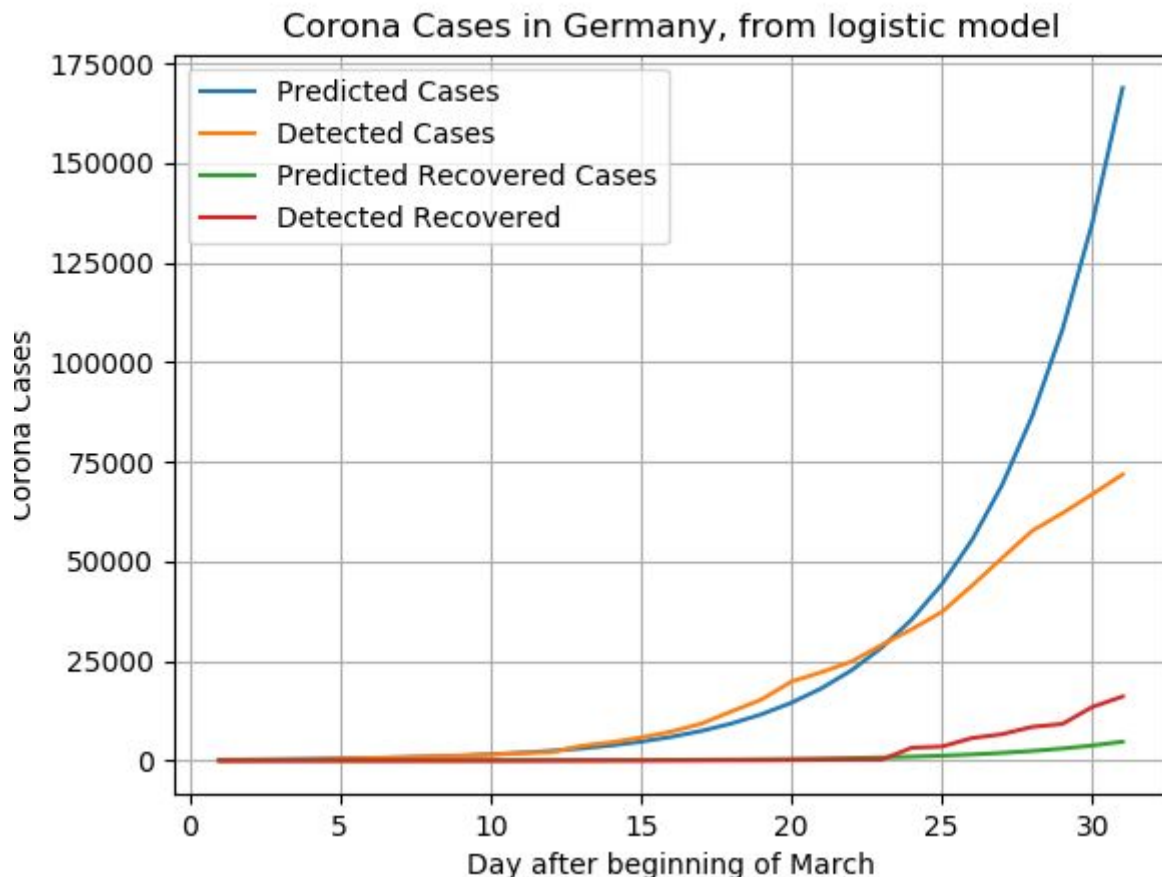
```
import urllib.request
import pandas as pd

url =
'https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/time_series_covid19_confirmed_global.csv'
urllib.request.urlretrieve(url, './corona_cases.csv')
df = pd.read_csv('./corona_cases.csv')
```

Since we now have the beginning of April, we can compare the month of March. We let the program run with

```
python3 coronacasesreview.py
```

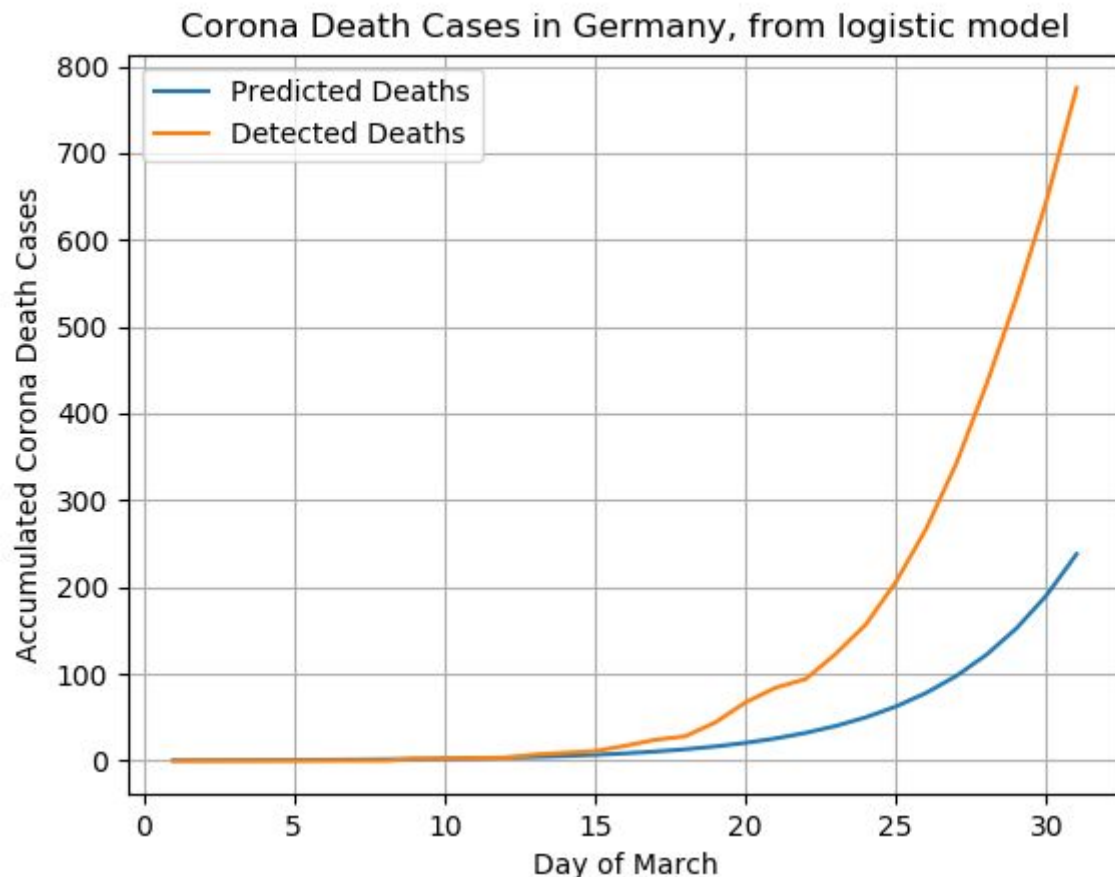
First we see a numerical printout of the data, then a plot of the detected cases and the recovered,



Compare the **predicted cases** and the **detected cases**: Around **March 20**, the slope becomes **noticeably lower**. This was the day when the main restrictions for social distancing were imposed. From this plot we can estimate that the social distancing **saved about 70000 infections** until March 30.

Observe the **recovered cases**: at around March 23, the number of recovered increases clearly faster than the model predicted. This probably comes from a **reduced time from detection to recovery or death**, probably from a **later detection** of cases.

Here are the death cases from the model and the data,



Observe that the true death cases are significantly above the prediction from the model. This can also be explained by the reduced time from detection to recovery or death.

We can **estimate** the **time from detection to recovery or death** from the data (which shows in the terminal output of the program) in late March:

**March 31:** 16100 recovered, 775 deaths, total= 16875. Find a similar higher number for the detected cases (to see where they came from):

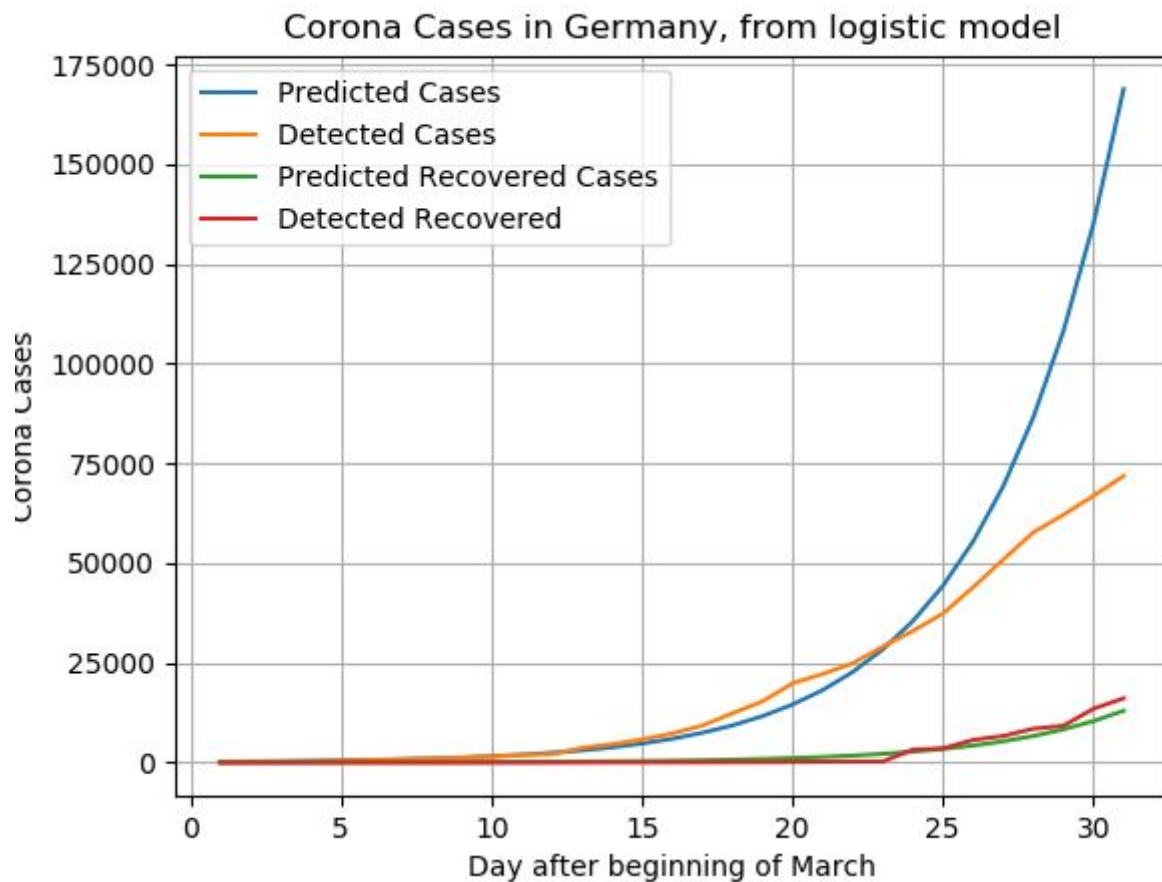
**March 19:** 15320

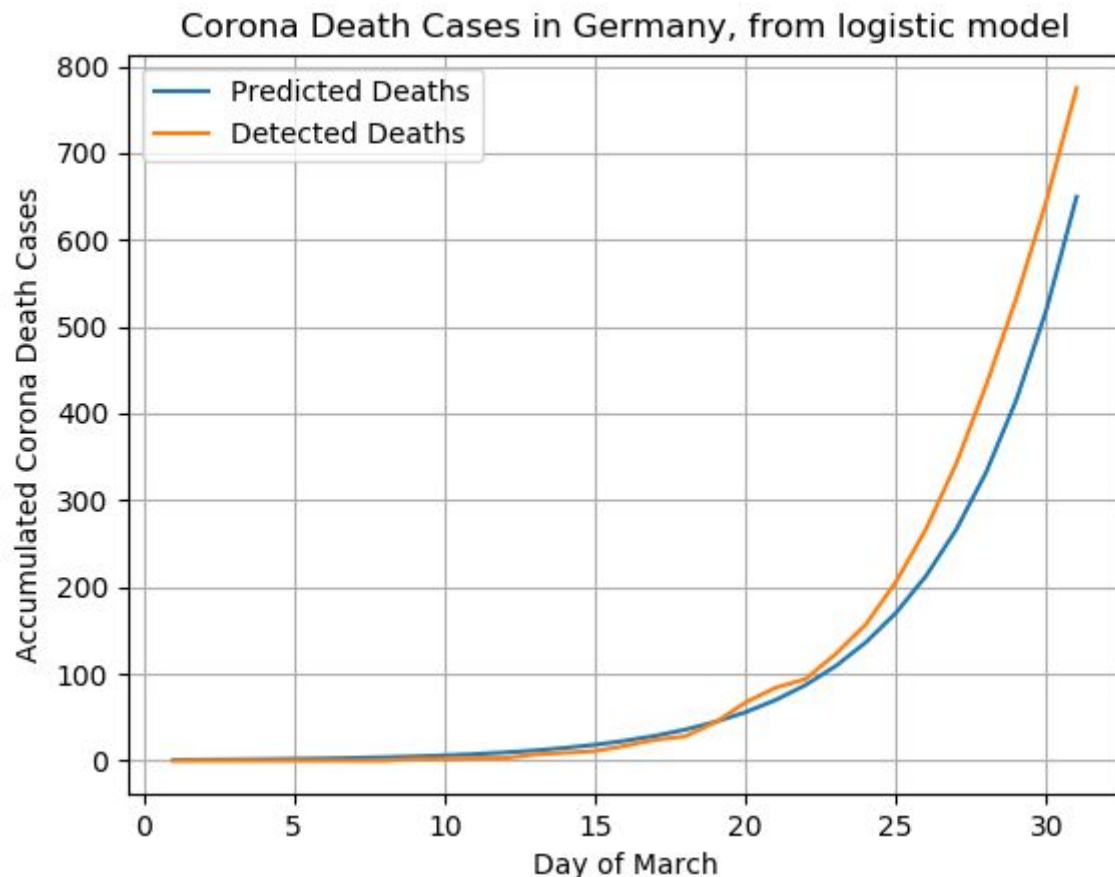
**March 20:** 19848

Hence, from March 19 or 20 to March 30 we have ca. **11.5 days** from detection to recovery or death. (instead of 16 days in the first half of March).



We can verify this updated time from detection to recovery or death in our program, and plot again to see if it fits,





For the recovered and the deaths we indeed get a **better match** for the second half of March, although the deaths are still somewhat underestimated in the end.

Using these numbers (775 deaths, 16100 recovered on March 31st) we can now compute a **detected case based mortality rate** of  $775/(16100+775)=4.6\%$ . This is higher than the infection based mortality rate of about 2%, because **not all infected are detected**.

This also means we have an **under-detection rate** of  $4.6\% / 2\%=2.3$ . This is not bad.

Hence the true number of infected should be roughly a factor of 2.3 higher than the detected cases. This depends on the testing rate.

The **testing rate** is quite different in different countries, which can be seen in this table:

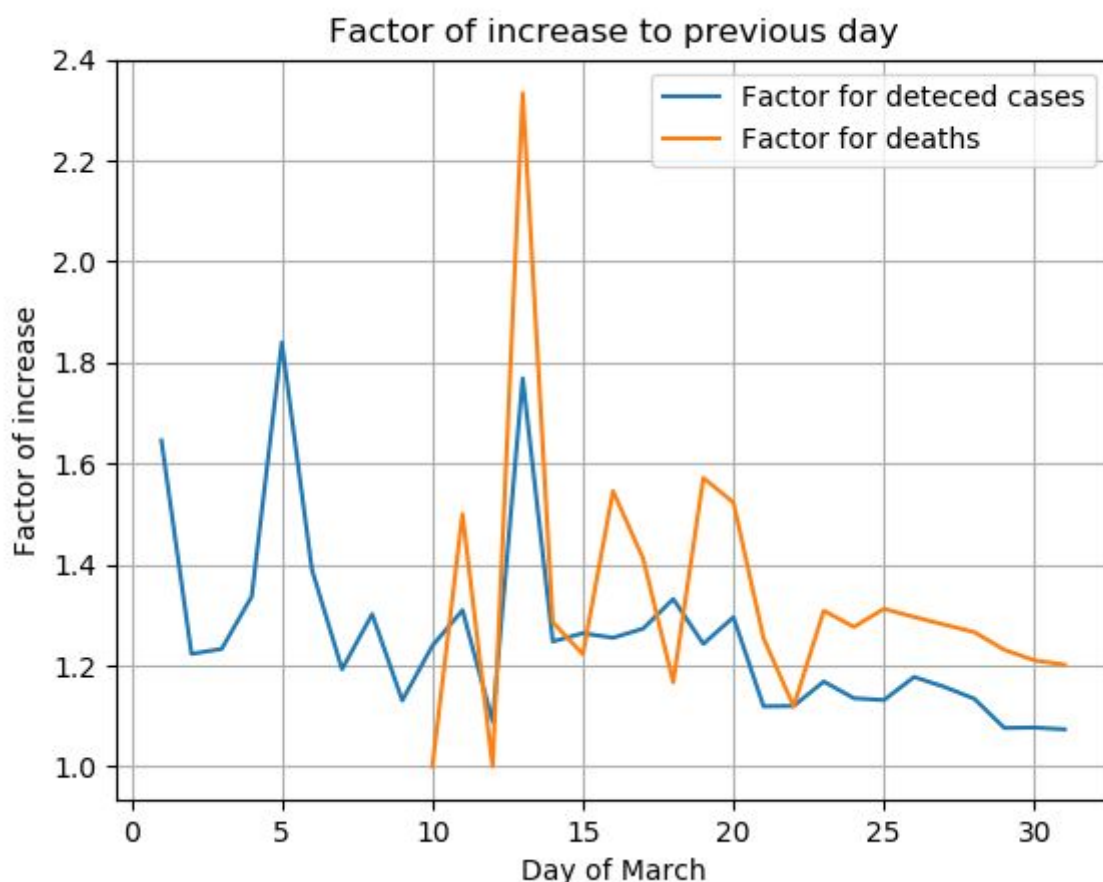
[https://en.wikipedia.org/wiki/COVID-19\\_testing](https://en.wikipedia.org/wiki/COVID-19_testing)

And sort the table for “Tests / million people”.

As can be seen there, Germany is in a relatively good position.

### Factor of Daily Increase:

Using our data we can now compute and plot the daily factor of increase  $f$  for the detected cases and the deaths for March,



We see: in the **first half of March**, this factor for the cases fluctuated a lot, partially because the numbers were still small.

The factor for the deaths begins in March 10th with the first death, and it can be seen that it lags behind the number of cases by about 10 days.

We see: the model's previous value of 1.25 for the detected cases was more on the low side. Starting March 20, this factor became clearly lower, and on March 31 was at **1.075**. This is **much better**.

**How many days**  $t$  does it take to **obtain a doubling** with this factor?

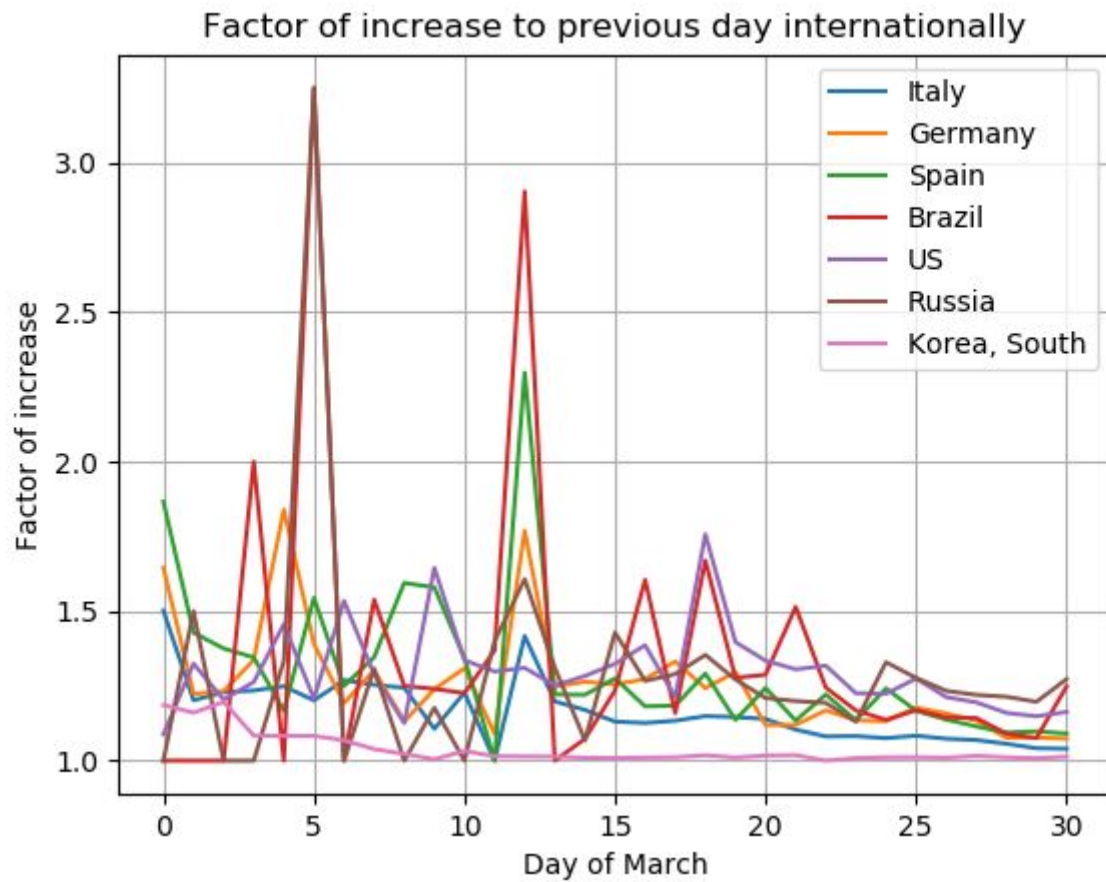
$$1.075^t = 2$$

$$t \cdot \log(1.075) = \log(2)$$

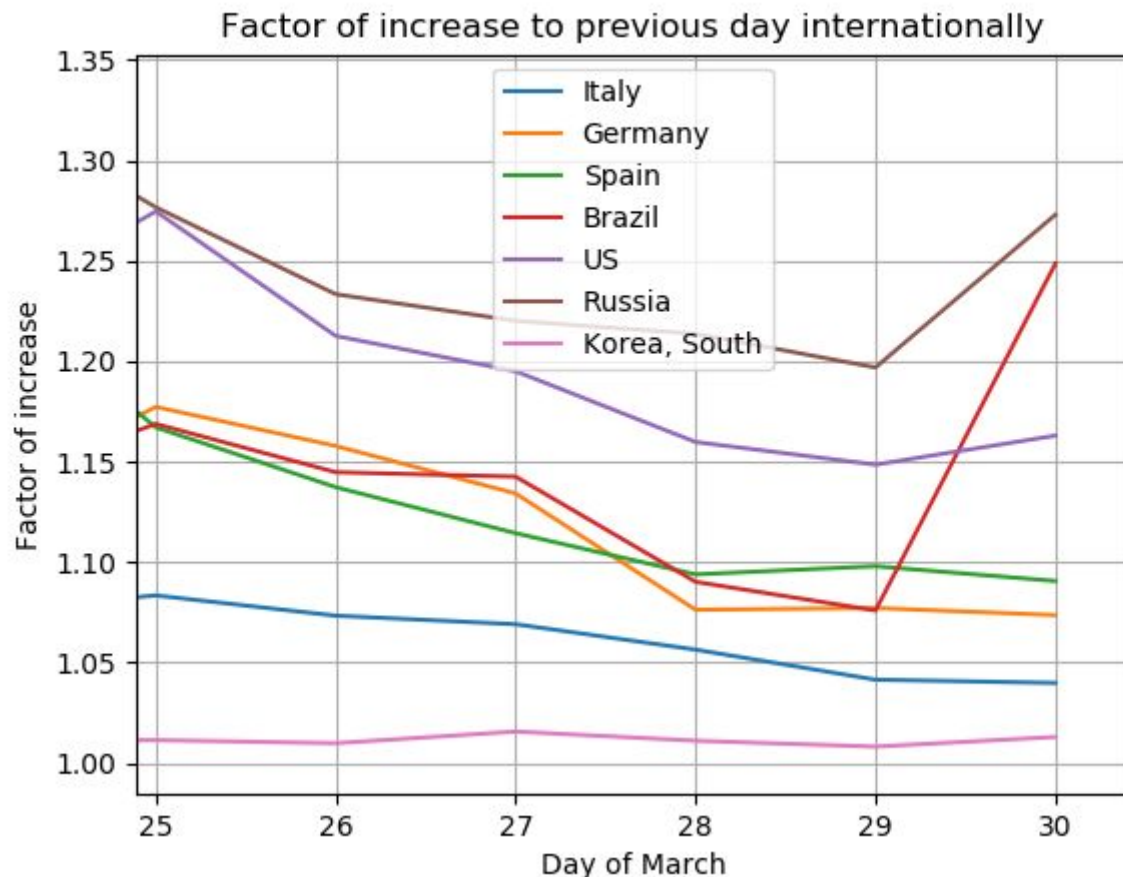
$$t = \log(2) / \log(1.075) = \mathbf{9.6 \text{ days}}$$

With a factor of 1.075 we have a **doubling every 9.6 days**.

Factor of increase  $f$  for different countries:



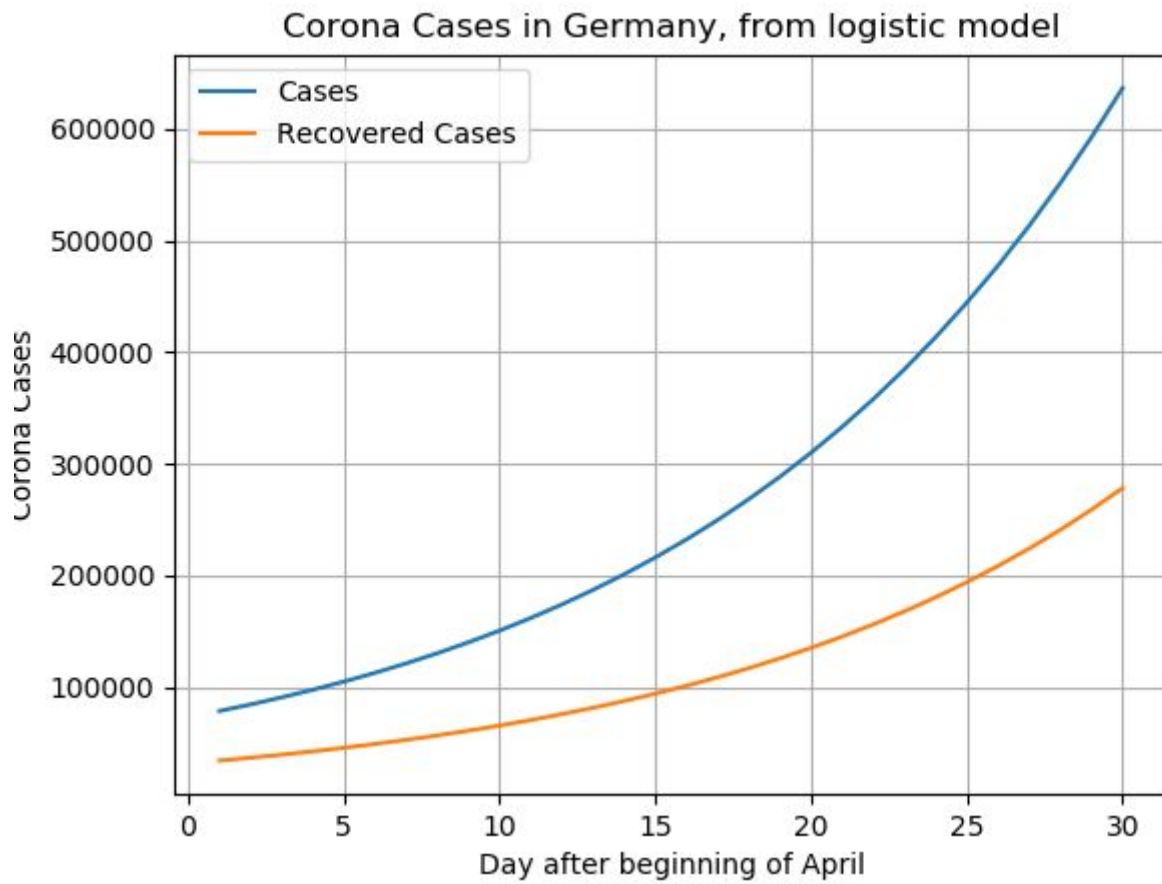
Zoomed into the lower right part:



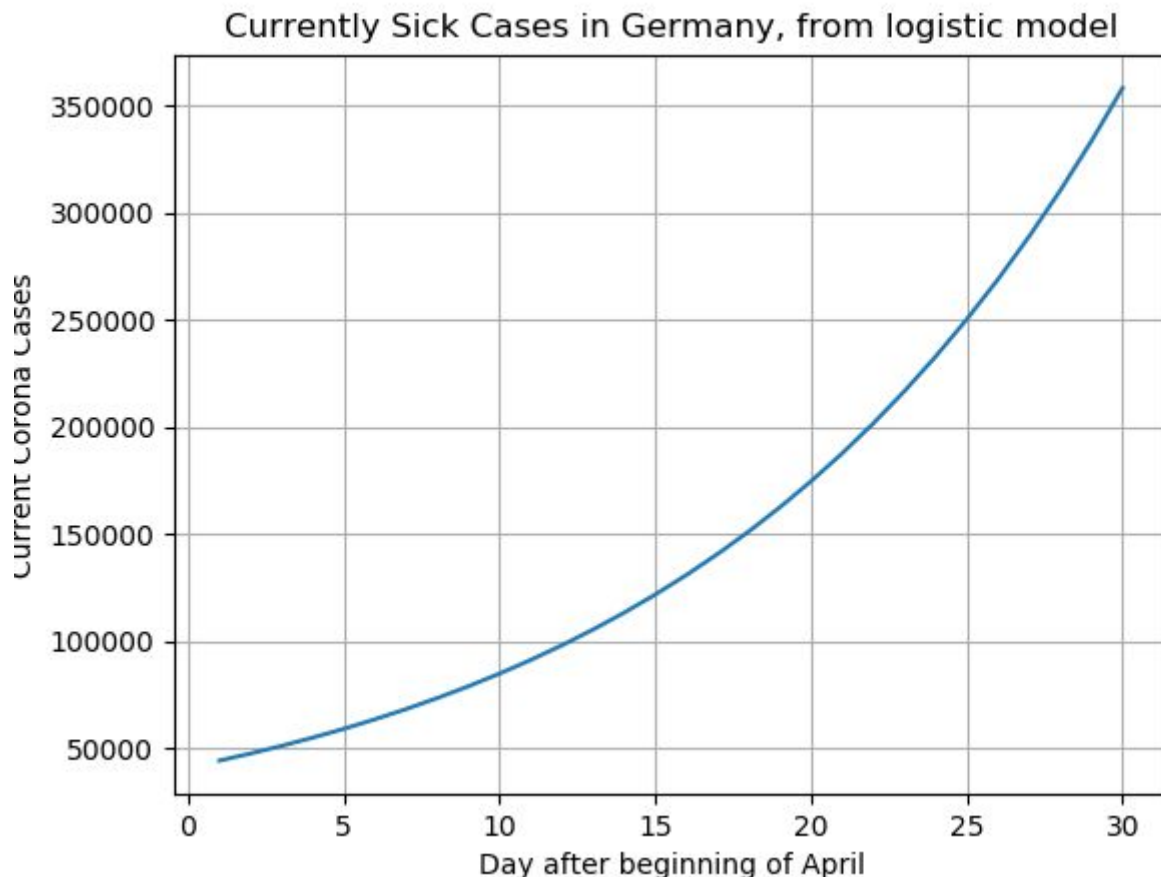
Observe: **South Korea indeed achieved my target of 1.02!**

These **updated numbers** and a **new data point** of the number of **cases for April 2nd** are now used to **update the model** and make predictions for Germany for April.

The detected cases,



The (con)currently sick,



This is interesting for the

**Rate of intensive care:**

According to

<https://www.statnews.com/2020/03/10/simple-math-a-larming-answers-covid-19/>

It also says the infection based mortality is 2%, and the rate for intensive care is 5%, a factor of  $5\%/2.5\%=2.5$  higher than the mortality.

This means we get a **case based rate for the intensive care** in Germany of  $2.5 \cdot 4.6\% = 12\%$ .

According to

<https://daserste.ndr.de/panorama/archiv/2020/Corona-Krise-Wann-kommt-der-Klinikkollaps.corona1430.html>



We have 15000 intensive care beds reserved for Corona cases. If 12% of the currently sick require intensive care, this corresponds to

$$15000/0.12=\mathbf{125000 \text{ currently sick cases}}$$

This means, if the number of currently sick cases reaches 125000, our intensive care units **reach their capacity**.

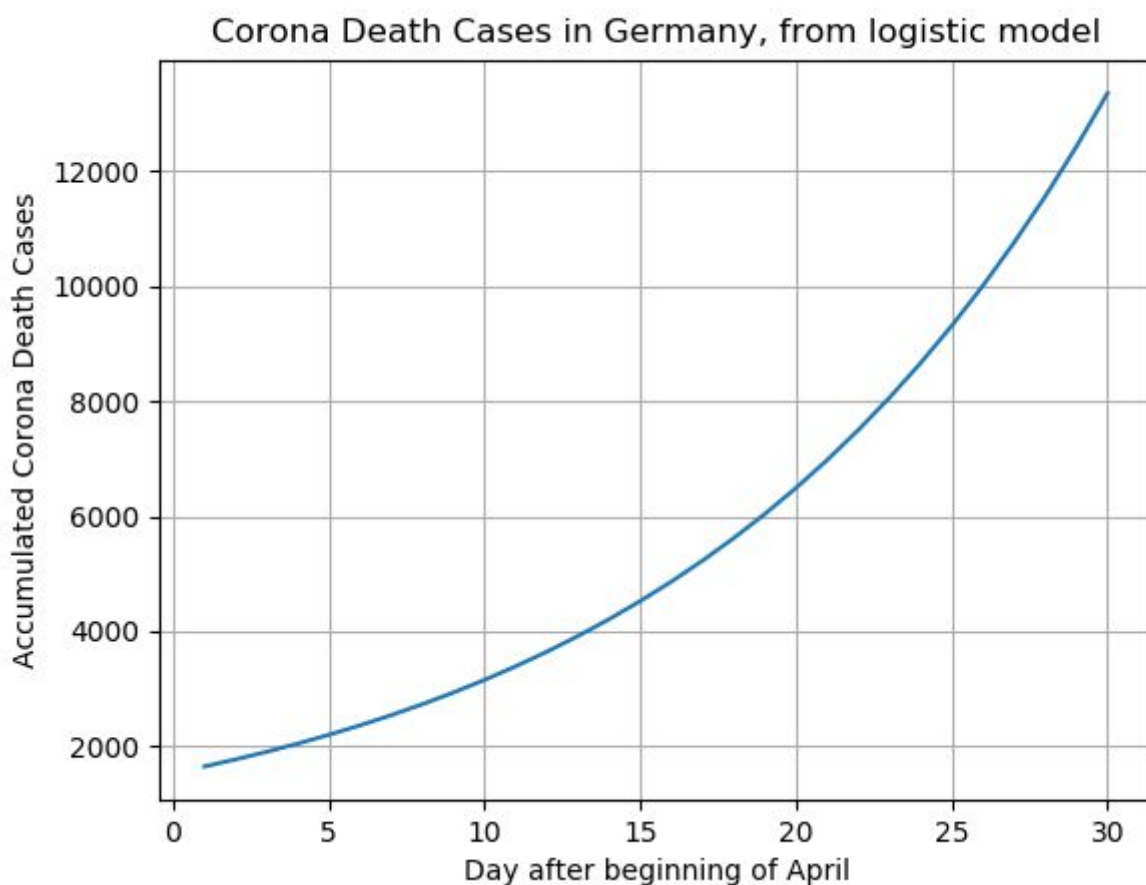
According to the plot above, this will be around **April 15**.

This is bad.

To avoid this, the **daily factor of increase of 1.075 needs further reduction**.

In my last video I concluded the factor needs to be at **f=1.02** (doubling in ca. 35 days).

The number of deaths:

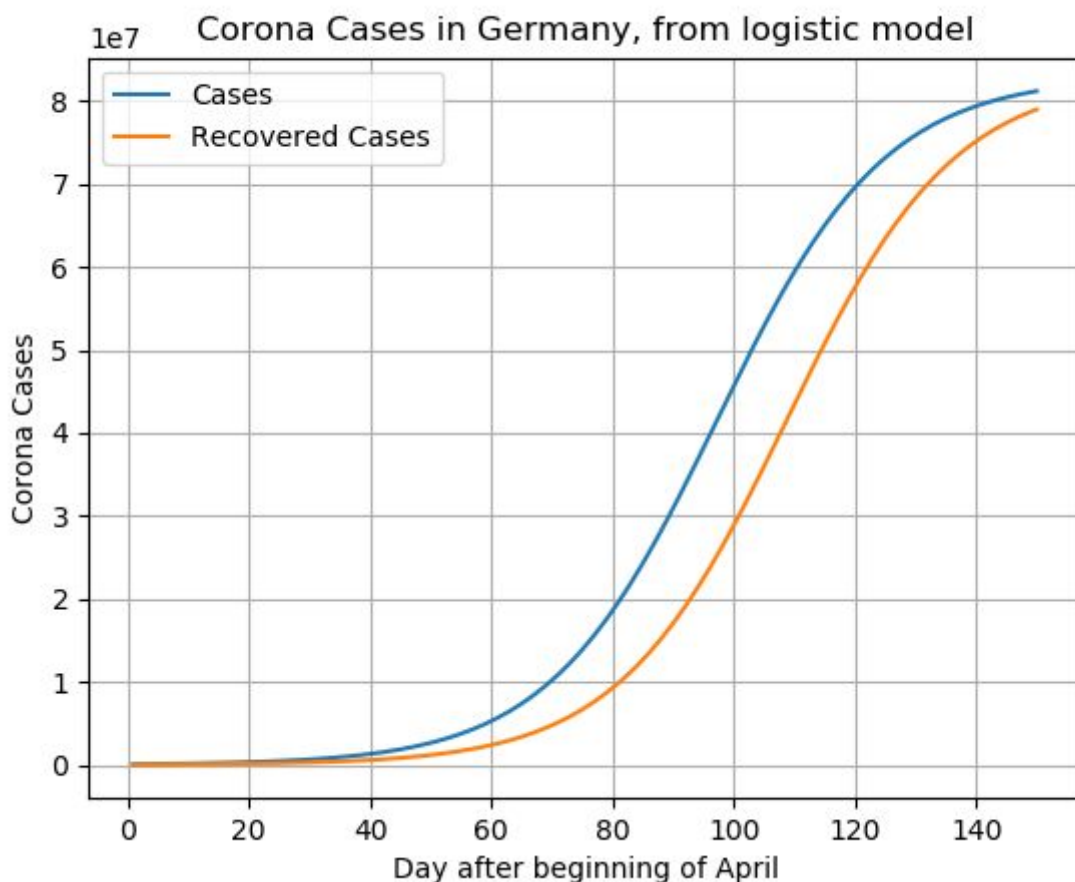


We see: The last 20 days of April we would get about 10000 additional deaths, about 500 a day. This is a lot.

## Long Term Prediction

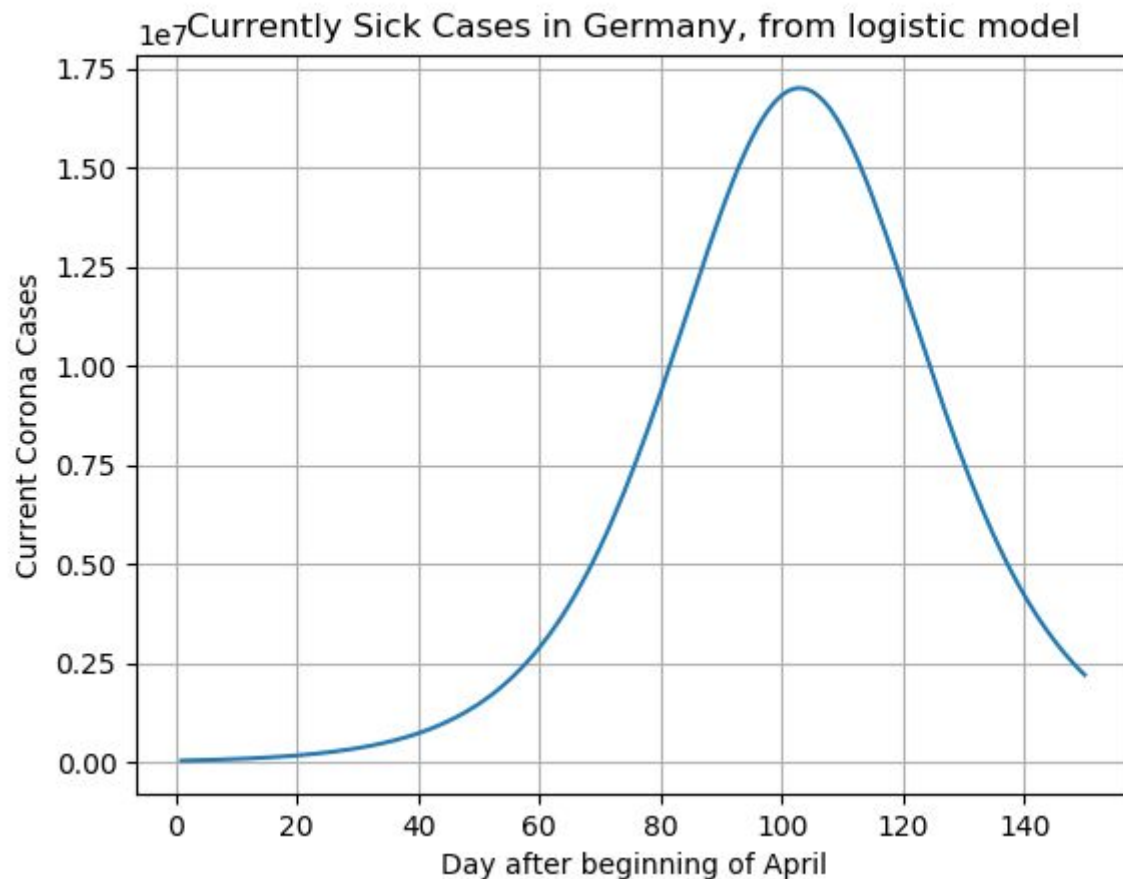
Using the parameters from the beginning of April, we can now let the model run for a prediction over 150 days, starting April 1st.

**The detected and recovered cases:**



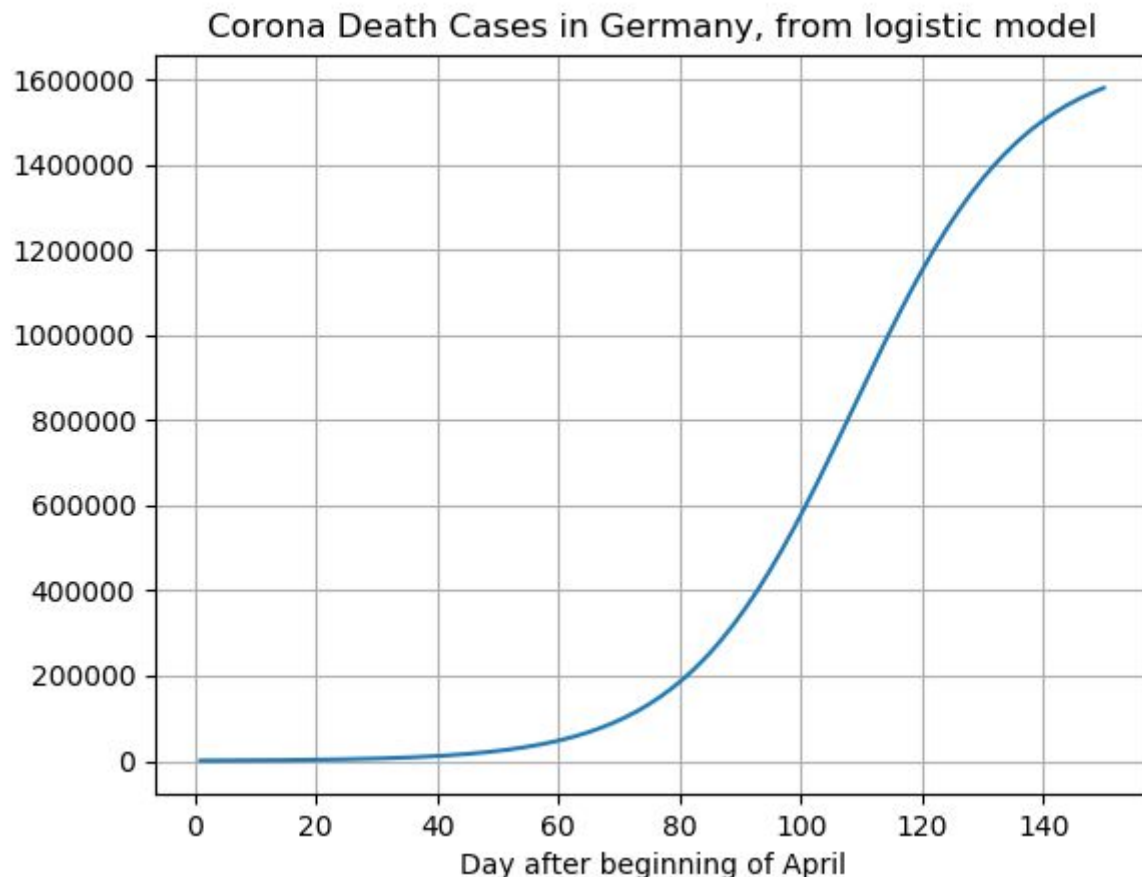
We see: after about 140 days, practically everybody would be infected. This is bad.

The (con)currently sick:



We see: There is a big peak 100 days after the beginning of April, hence beginning of July, where we get about **17 Million people sick at the same time**. This is much too much.

The deaths cases:



We see:

- it predicts about **1.6 Million deaths** in Germany in the end, much too much.
- In comparison: a very bad seasonal flu year in Germany has an excess mortality (all deaths above the long term average) of about 25000. A normal flu year has just about 200.
- This number is **independent of the rate of increase** and only dependent on the **infections based mortality rate (assumed 2%)**
- with a possible range of the mortality rate of 0.6% to 5% this would be 498000 to 4.15 Million deaths.
- Hence it is best to **slow the spread until we have a vaccine.**

This shows that we really need to reach the **daily factor of increase of 1.02 (doubling in roughly 35 days)**, which I showed in my last video, with **social distancing**, and also with **comprehensive testing** to effectively quarantine each infected person, like in South Korea.

**South Korea** could be a good **role model**, because they **reached this factor**, and managed to almost stop the spread, without much restrictions.

### **Conclusions:**

- Mathematical models, data, and programming allow effective **predictions**.
- We are on the right track **slowing the spread** of the new Corona virus, but not quite there to avoid overloading our hospitals.
- We need to slow the spread **until we have a vaccine**, to avoid high death counts.
- An important part of a solution to slow the spread is **comprehensive testing**, as in South Korea, which **allows loosening restrictions**.