Corona Datathon

Team: C.F.R.S.S.

Member:

Giona SALA
Antoine SUTER
Philipp RUPP
Leonardo FOSSATI
ManHin CHENG

Overlook

- Growth Models
- Demographics
- Mobility
- A more advanced model
- Linear Regression

Logistic Growth Model

$$\boxed{Q_t = \frac{a}{1+e^{b-c(t-t_0)}}} \Leftarrow \frac{df(t)}{dt} \propto f(t)(1-f(t))$$

a = max. cases

b = initial condition

c = rate of growth

[1] Jia et al. 2020, Prediction and analysis of Coronavirus Disease 2019

Gompertz Growth Model

$$\boxed{Q_t = ae^{-be^{-c(t-t_0)}}}$$

$$k^{\frac{f'(t)}{f(t)}} \propto \frac{1}{f(t)}$$

a = max. cases

b = displacement

c = rate of growth

[1] Jia et al. 2020, Prediction and analysis of Coronavirus Disease 2019

Bertalanffy Growth Model

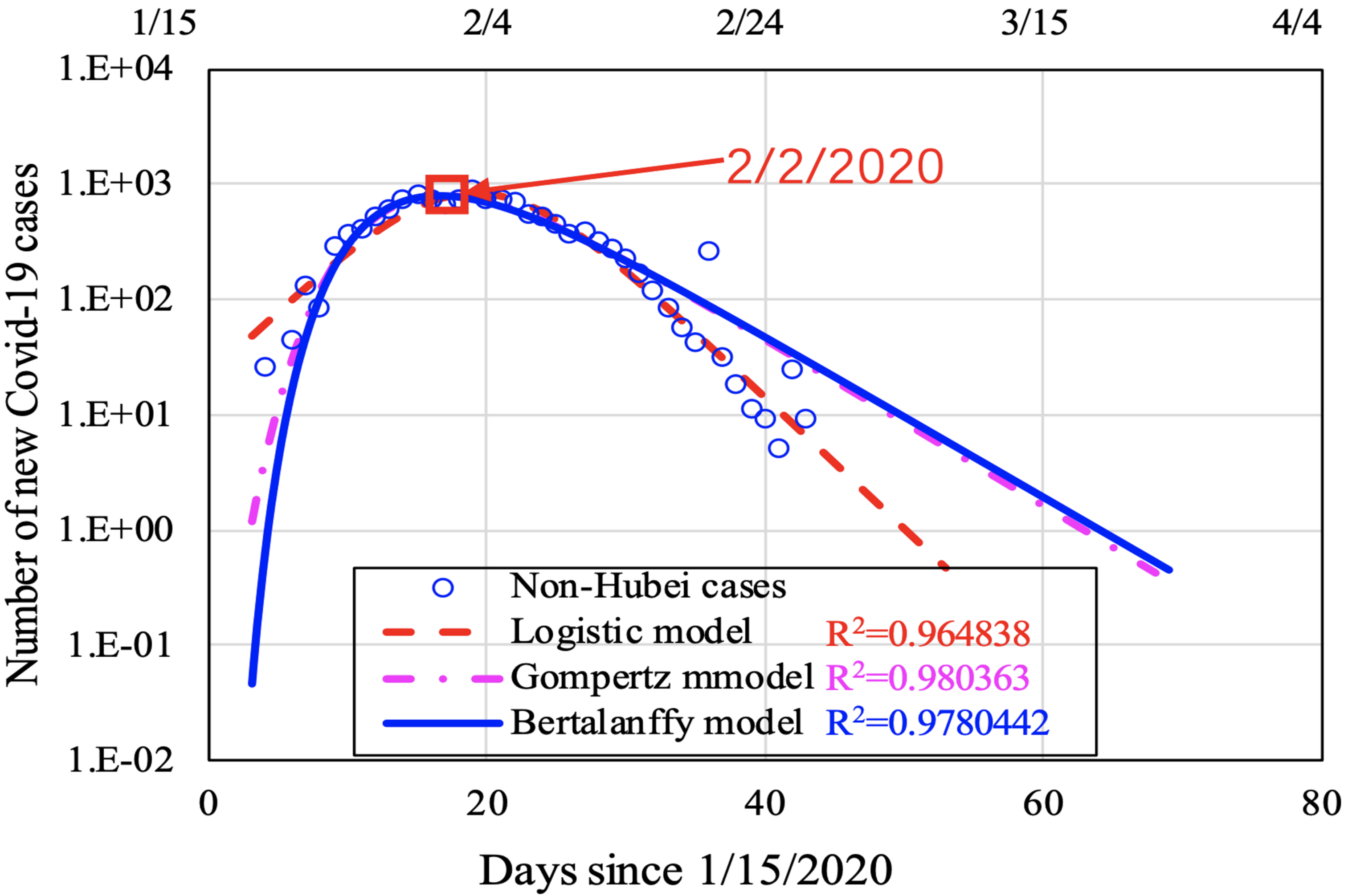
$$\boxed{Q_t = a\left(1 - e^{-b(t-t_0)}\right)^c} \Leftarrow \frac{df(t)}{dt} \propto f_{t\to\infty} - f(t)$$

a = max. cases

b = asymptotic growth

c = rate of growth

[1] Jia et al. 2020, Prediction and analysis of Coronavirus Disease 2019



[1] Jia et al. 2020, Prediction and analysis of Coronavirus Disease 2019

Demographic influence

Assumption:

- Countries with older population are more susceptible to the virus and should present a larger mortality rate
    - Mortality rate is different depending on age group

Main Problem:

- Different countries have similar cases distribution by age group

Demographic influence

1. Calculate total number of cases [1]:
    - Everyone has the same probability to be infected
        - Mortality rate by age is based on confirmed cases

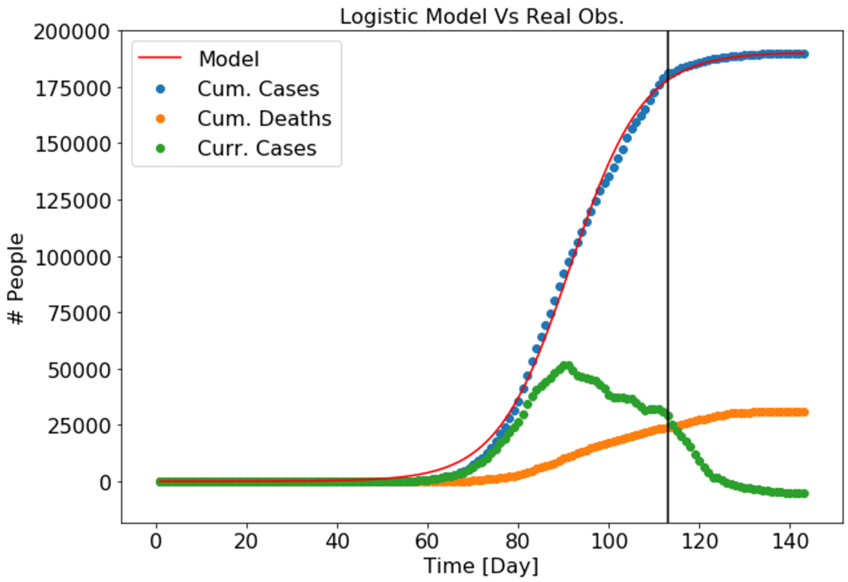
1. Dynamics of populations [2]:
    - Contact between different age groups
    - Family structures and cultures
        - Lack of data

[1] Lachmann, Alexander & Jagodnik, Kathleen M. & Giorgi, Federico Manuel & A. Ray, Forest. *Correcting under-reported COVID-19 case numbers: estimating the true scale of the pandemic*, 2020. medRxiv. doi: 10.1101/2020.03.14.20036178. https://www.medrxiv.org/content/medrxiv/early/2020/04/05/2020.03.14.20036178.full.pdf

[2] Wilder, Bryan & Charpignon, Marie & Killian, Jackson & Ou, Han-Ching & Mate, Aditya & Jabbari, Shahin & Perrault, Andrew & Desai, Angel & Tambe, Milind & Majumder, Maimuna. *The Role of Age Distribution and Family Structure on COVID-19 Dynamics: A Preliminary Modeling Assessment for Hubei and Lombardy*, 2020. SSRN Electronic Journal. doi: 10.2139/ssrn.3564800.

Demographic influence

Simple model which predicts the number of deaths based on confirmed cases and the average of mortality rate works better



Health system capacity

Assumption:

- Mortality rate increases drastically when the health system is at capacity

Problems:

- Lack of data
- Not really relevant until a second wave

Mobility model

1. Understand and reproduce the spatial spread of an infectious disease epidemic → more relibable predictions: Pivotal Point

1. Already implemented in other studies (spread of previous SARS, Seasonal Influenza-like-illness -ILI, malaria diffusion) with outstanding results

1. Radiation model or mobile phone data model?

Mobilty pattern:
Residence place - Workplace

Mobilty pattern:
All movements of a single individual recorded by mobile phone

Radiation model: a simple, but powerful tool

1

goal: reproduce commuter movements

2

based on stochastic decision process:

assigns work location to each potential commuter → daily commuting fluxes in a country

3

being free-parameter: absence of empirical data to be fitted or regression analysis in details : networks is generated by creating a fully connected topology between country's locations, where the weight between nodes i-j:

$$\boxed{w_{ij}^{r} = \frac{N_i N_j}{(N_i + P_{ij})(N_i + N_j + P_{ij})} \sum_{j \neq i} w_{ij},}$$

- N_i (N_j) population of origin (destination)
- P_{ij}: total population living between i and j
- E: w_{ij}: total number of commuters leaving their home in location i.

It requires: 1. knowlegde of population data (N_i, N_j, P)

2. total number of residents who commute in each administrative unit

Mobility model - Radiation model

Problems:

1. Only house-work pattern taken into account → LIMITATION?

1. Data for calibration: data of the census → accessibility? Lack of data

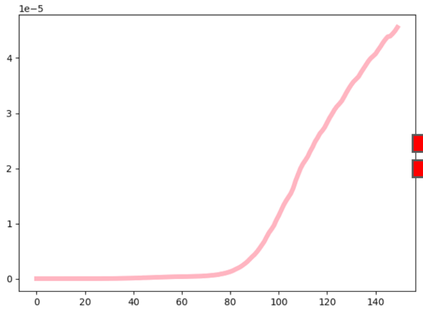
But very promising!

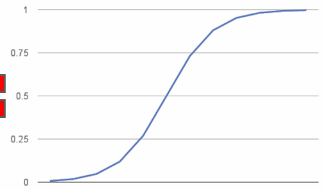
Our Complex Model

Aspects:

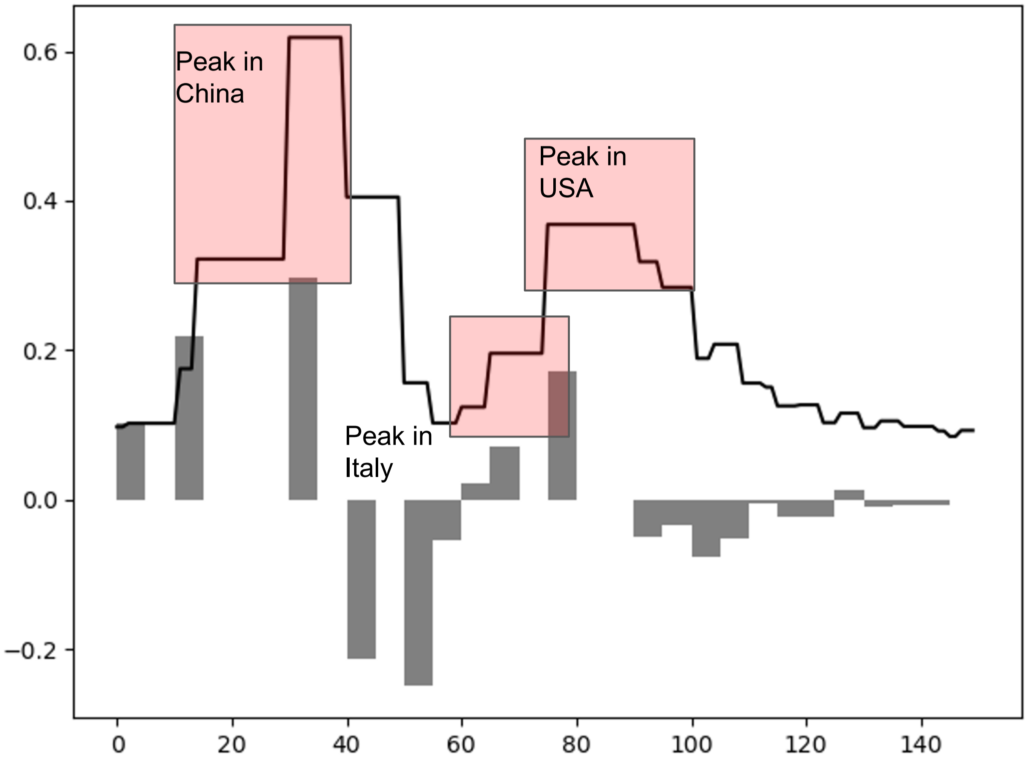
- Logistic Model
- Takes into isolation/mobility into account
  - With prediction of political decisions: could even model a second wave
- Based on recorded deaths to predict future

```
    #mod.addPopChange([0, np.random.lognormal(-2.0, 0.5)])
    return mod

# ==========================================================================
# generates a child that has similar traits(parameters) like parent
# ==========================================================================
def mutation(self):
    # change parameters of model
    child = copy.deepcopy(self)
    rand = np.random.normal(0, 0.01,
                            len(child.evalParam))  # mu = 0 and sigma = 0.01 so that the change is roughly 4 %
    child.evalParam += np.multiply(rand, child.evalParam)

    attemps = np.random.uniform(0, 1, min(np.random.lognormal(0.5, 0.5), 10))
    for a in attemps:
        if a < 0.5:
            if np.random.uniform(0, 1) < 0.5:
                child.addPopChange([np.random.uniform(0, child.maxIter), np.random.normal(0.0, 0.003)])
            else:
                child.multPopChange([np.random.uniform(0, len(child.popChangeList)), np.random.normal(1.0, 0.007)])

# ==========================================================================
# adds a change to the list that contains daily changes
# ==========================================================================
def multPopChange(self, change):
    day = int(change[0])
    factor = change[1]
    if day > self.maxIter:
      return False
     factor <= 0.0:
      self.delPopChange(day)
      return True
     if self.popChangeTotal * factor >= 1.0:
      factor = 1.0 / self.popChangeTotal
     pChange = self.popChangeTotal * (factor - 1.0)
     lf.__addPopChange__([day, popChange])
     lf.popChangeList.sort(key=lambda x: x[0])
     turn True

     dPopChange(self, change):
     y = int(change[0])
     pChange = change[1]
```

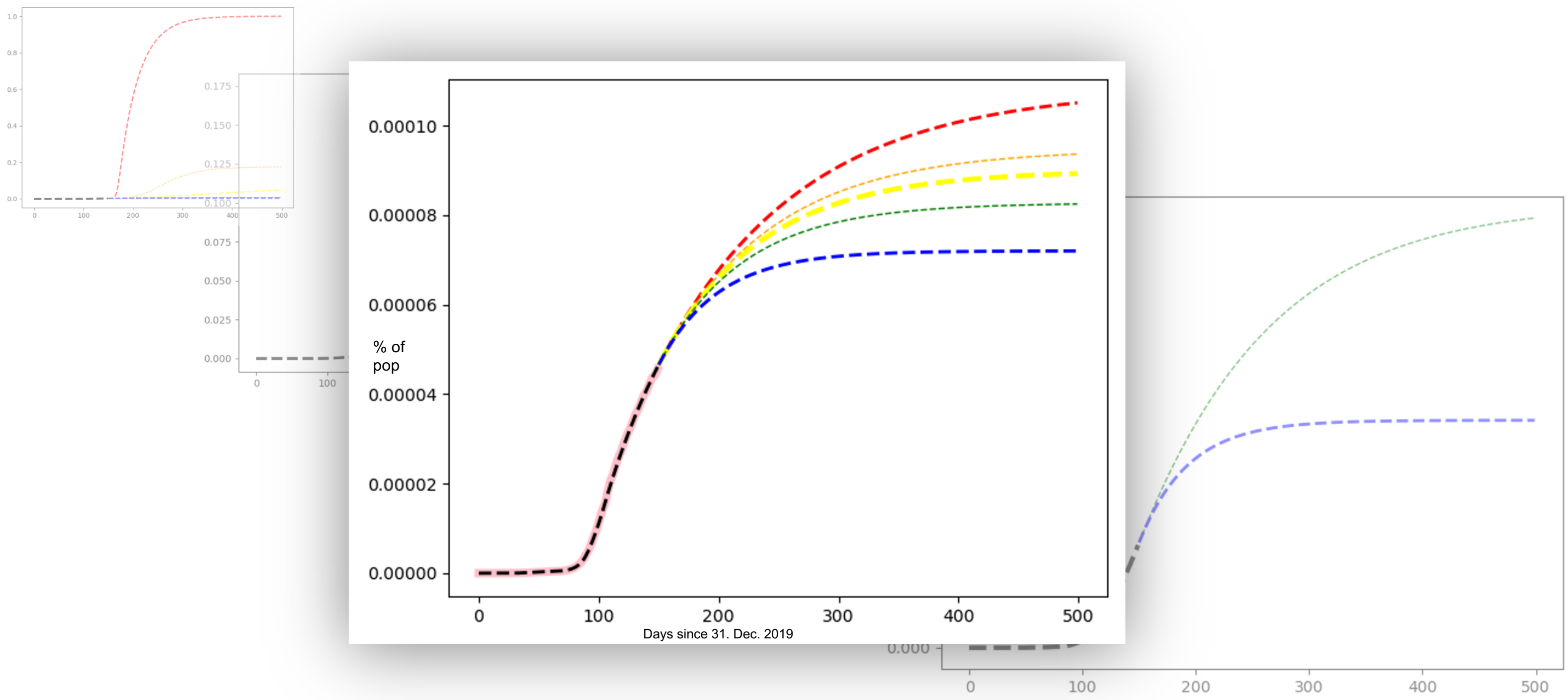




Susceptibility; Summarized in numbers



Predictions are sensitive



Linear Regression

- K.I.S.S: Keep It Simple Stupid
- **Short memory Markov chain** process (5 day)
- **y = mx + C**

Day 1 to Day 5 → Day 6

Day 2 to Day 6 → Day 7

Day 3 to Day 7 → Day 8

Day 4 to Day 8 → Day 9

Day 5 to Day 9 → Day 10

Linear Regression

Confirmed ≥ Recovered + Death

- Random noise to constrain it

Weekly Leaderboard

2 Day

Leaderboards are displaying weekly scores (higher is better). A new competition starts every Sunday. More information here. Teams with excellent prediction performances (winners of a 2day competition receive 🏆, winners of a 7day competition receive 🔮, winners of a 30day competition receives 🥇) will be selected for feature stories in our Epidemic Datathon blog.

SCORE	TEAM
1530.7537906116497	C.F.R.S.S.
1500.9833290323852	GNTM_team
1239.7495485032903	stayhome
86.31297300098026	Quarenteam
5.960541171537382	ValenciaSpain

Weekly Leaderboard

7 Day

Leaderboards are displaying weekly scores (higher is better). A new competition starts every Sunday. More information here. Teams with excellent prediction performances (winners of a 2day competition receive 🏆, winners of a 7day competition receive 🔮, winners of a 30day competition receives 🥇) will be selected for feature stories in our Epidemic Datathon blog.

SCORE	TEAM	WINS
1443.5828241598147	C.F.R.S.S.	4x🏆,3x🔮,1x🥇
1403.3621904160848	GNTM_team	2x🏆,3x🔮,1x🥇
1350.3324663589149	stayhome	2x🏆,2x🥇
236.83130580111398	Quarenteam	
4.740510622861562	ValenciaSpain	1x🥇

Weekly Leaderboard

30 Day

Leaderboards are displaying weekly scores (higher is better). A new competition starts every Sunday. More information here. Teams with excellent prediction performances (winners of a 2day competition receive 🏆, winners of a 7day competition receive 🔮, winners of a 30day competition receives 🥇) will be selected for feature stories in our Epidemic Datathon blog.

SCORE	TEAM	WINS
1129.6288197582976	C.F.R.S.S.	4x🏆,3x🔮,1x🥇
1033.8505508083854	GNTM_team	2x🏆,3x🔮,1x🥇
857.9139149953027	stayhome	2x🏆,2x🥇
92.01576321396347	Quarenteam	
12.098753122499492	BuZhunBieXin	
2.2958006003576887	ValenciaSpain	1x🥇

Thank you for your attention