Global Short-Term Forecasting of Covid-19 Cases

Thiago de Paula Oliveira
thiago.paula.oliveira@insight-centre.org
https://prof-thiagooliveira.netlify.com

Rafael de Andrade Moral
rafael.deandrademoral@mu.ie

30th July 2020

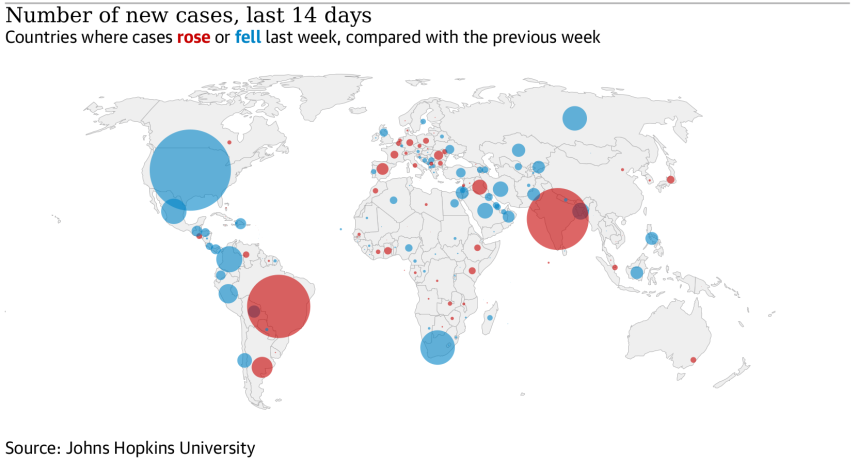
NUI Galway
OÉ Gaillimh

Maynooth University
National University of Ireland Maynooth

Contents

Introduction and Motivation

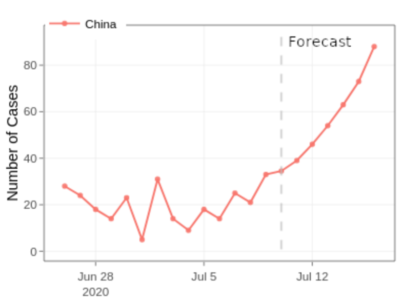
- The virus, which causes the respiratory infection Covid-19, was first detected in the city of Wuhan, China, in late 2019.
- Social and Economic Impact

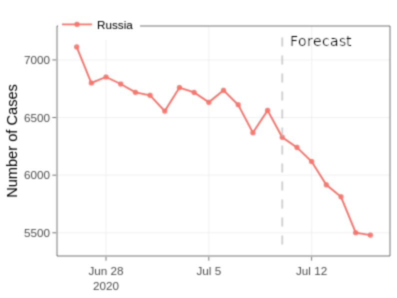


Introduction and Motivation - Forecast Models

- New disease with many factors acting in concert:
  - Spreading with great speed
  - Human behaviour
  - Government intervention/policies
  - Data quality - number of cases did not reflect correct numbers

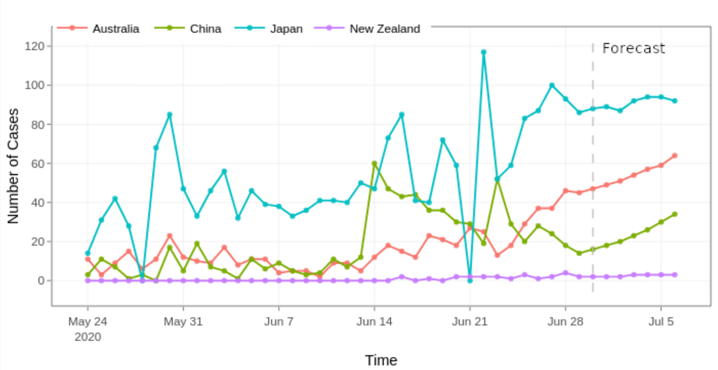
- Forecasting with great accuracy under these circumstances is very difficult, and, consequently, would prove itself invaluable





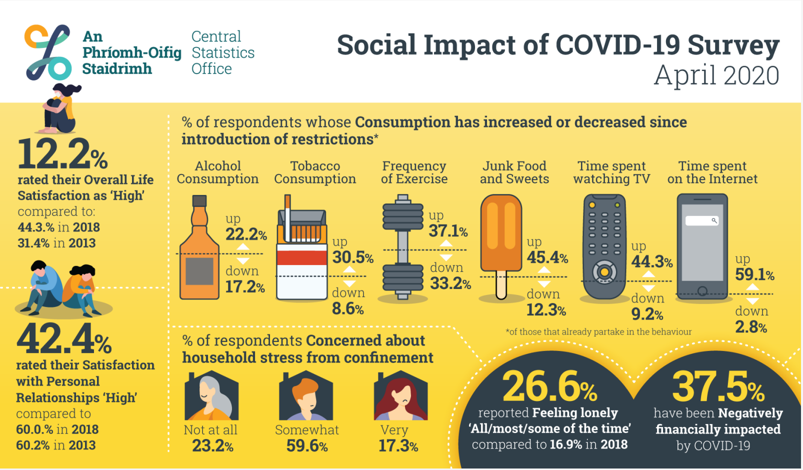
Introduction and Motivation - Forecast Models

- Short-term forecasts can give a good idea about the **trend** of the outbreak, and **can be crucial to assist planning**
- Could help low-and-middle-income countries/cities
- Develop **strategic planning** in the public health system to **avoid deaths**



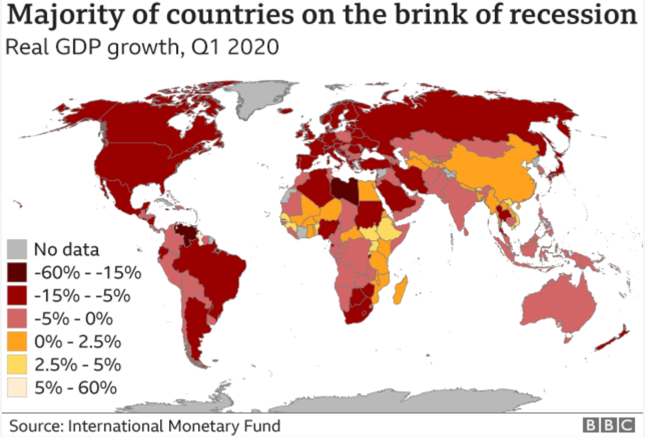
Introduction and Motivation - Social Impact

- Impact COVID-19 has had on Irish society in April 2020
- Sample of 4,033 persons 18 years and over



Introduction and Motivation - Economic Impact

- Outbreaks of the COVID-19 pandemic have been causing worldwide socioeconomic and health concerns



- IMF says that the global economy will shrink by 3% this year

Objectives

- Propose a new modelling framework to handle with the behaviour of reported number of cases by country
  - State-space hierarchical model
  - Generate forecasts with very good accuracy for up to seven days ahead
- Propose clustering the countries based on the behaviour of their estimated autoregressive parameter over the last 60 days
- Provide all results as an R Shiny Dashboard
  - Including week-long forecasts for every country in the world
  - Point forecasts
  - Prediction intervals to express the uncertainty in the forecasts

Data and model access:

- https://github.com/Prof-ThiagoOliveira/covid_forecast

Data Acquisition

Data Acquisition

- European Centre for Disease Prevention and Control (ECDC)
- Data from the current day is removed, since it can be updated.

Data Acquisition

Table: Data structure

	dateRep	cases	deaths	countries	popData2019	continent
1	29/07/2020	103	1	Afghanistan	38041757	Asia
2	28/07/2020	105	1	Afghanistan	38041757	Asia
3	27/07/2020	106	10	Afghanistan	38041757	Asia
4	26/07/2020	121	13	Afghanistan	38041757	Asia
5	25/07/2020	108	35	Afghanistan	38041757	Asia
6	24/07/2020	13	0	Afghanistan	38041757	Asia
⋮	⋮	⋮	⋮	⋮	⋮	⋮

1. Number of Rows: $32,850$
2. Number of Columns: 6
3. countries is a factor with **210** levels

Methods

Modelling framework

- We introduce a class of state-space hierarchical models for overdispersed count time series

$$
\begin{aligned}
Y_{it} | Y_{i,t-1} &\sim \mathrm{NB}(\mu_{it}, \psi) \\
\log \mu_{it} &= \gamma_{it} + \Omega_{it} \\
\gamma_{it} &= \phi_{it}\gamma_{it-1} + \eta_{it}, \text{ with } \eta_{it} \sim \mathrm{N}\left(0, \sigma_\eta^2\right) \\
\phi_{it} &= \sum_{q=0}^{Q} (\beta_q + b_{iq}) P_q(t), \text{ with } \boldsymbol{b}_i \sim \mathrm{N}_Q\left(\mathbf{0}, \boldsymbol{\Sigma}_b\right) \\
\Omega_{it} &= \lambda_{it}\omega_{it}
\end{aligned}
$$

where $\lambda_{it} \sim \text{Bernoulli}(\pi)$ and $\omega_{it} \sim \mathrm{N}(0, \sigma_\omega^2)$.

- When $\lambda_{it} = 1$, then observation y_{it} is considered to be an outlier, and the extra variability is modelled by σ_ω^2

- ϕ_{it} varying by country: more flexible autocorrelation function
- Iterating γ_{it} we obtain

$$\gamma_{it} = \left(\prod_{k=2}^{t} \phi_{ik}\right) \gamma_{i1} + \sum_{j=2}^{t-1} \left[\left(\prod_{k=j+1}^{t} \phi_{ik} \right) \eta_{ij} \right] + \eta_{it} \tag{1}$$

for $t = 3, \ldots, T$.

- When $\phi_{it} = \phi_i = \beta_0 + b_{0i}$ (country-specific AR(1) process):

$$\gamma_{it} = \phi_i^{t-1}\gamma_{i1} + \phi_i^{t-2}\eta_{i2} + \phi_i^{t-3}\eta_{i3} + \ldots + \phi_i\eta_{it-1} + \eta_{it} \tag{2}$$

- When $\phi_{it} = \phi_i = \beta_0$ (same autocorrelation parameter):

$$\gamma_{it} = \phi^{t-1}\gamma_{i1} + \phi^{t-2}\eta_{i2} + \phi^{t-3}\eta_{i3} + \ldots + \phi\eta_{it-1} + \eta_{it} \tag{3}$$

Forecast future observations $y^*_{i,t+1}$

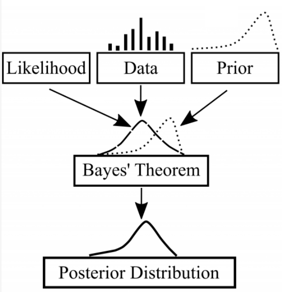
- Median of the posterior distribution of $Y_{i,t+1}|Y_{it}$.
- Reasonable for short-term forecasting
  - error accumulates from one time step to the other
- Seven days ahead

https://revenue-hub.com

Model implementation - Bayesian framework

The model is estimated using a Bayesian framework, and the prior distributions used are

$$
\begin{aligned}
\boldsymbol{\beta_i} &\sim \mathrm{N}_Q(\mathbf{0}, \mathbf{I}_Q \times 1000) \\
\sigma_{b_q}^{-2} &\sim \mathrm{Gamma}(0.001, 0.001) \\
\sigma_{\eta}^{-2} &\sim \mathrm{Gamma}(0.001, 0.001) \\
\sigma_{\omega}^{-2} &\sim \mathrm{Gamma}(0.001, 0.001) \\
\pi &\sim \mathrm{Uniform}(0, 1)
\end{aligned}
$$

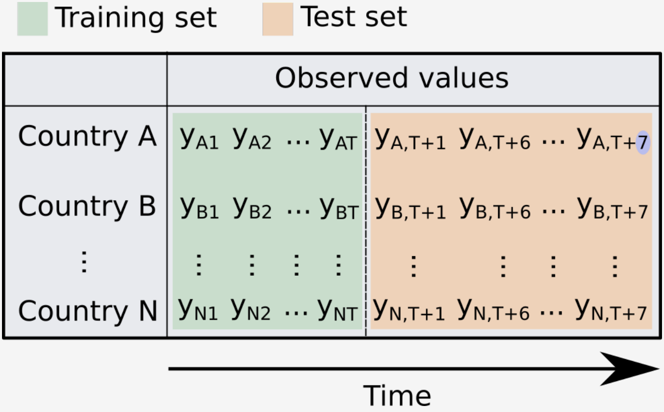


https://medium.com

- 3 MCMC chains
- 2,000 adaptation iterations
- 50,000 as burn-in
- 50,000 iterations per chain with a thinning of 25

Model Validation

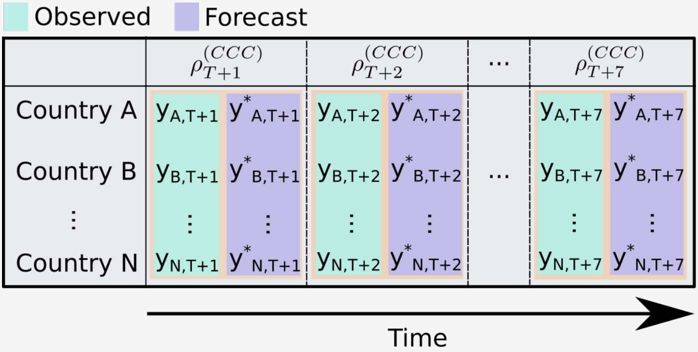
- Last seven observation by country as test set



- Compared the forecasts with the true observations y_{it} for each day ahead;

- Concordance correlation coefficient (Lin, 1989)
- ρ - Pearson Correlation Coefficient (precision)
- C_b - bias corrector factor (accuracy)

$$\rho_t^{(CCC)} = 1 - \frac{\mathrm{E}\left[\left(Y_t^* - Y_t\right)^2\right]}{\sigma_1^2 + \sigma_2^2 + (\mu_1 - \mu_2)^2} = \frac{2\sigma_{12}}{\sigma_1^2 + \sigma_2^2 + (\mu_1 - \mu_2)^2} = \rho C_b$$



Clustering

- Aim: obtain sets of countries that presented a similar recent behaviour
- Last 60 values of the estimated autoregressive component

Clustering

- Aim: obtain sets of countries that presented a similar recent behaviour
- Last 60 values of the estimated autoregressive component

Dynamic time warp (DTW) - Muller (2007)

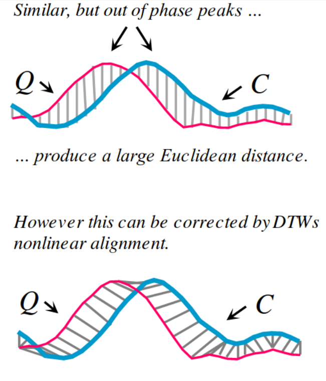
Let M be the set of all possible sequences of m pairs preserving the order of observations in the form $r = ((\hat{\gamma}_{i1}, \hat{\gamma}_{i'1}), \ldots, (\hat{\gamma}_{im}, \hat{\gamma}_{i'm}))$.

- minimise the distance between the coupled observations $(\hat{\gamma}_{it}, \hat{\gamma}_{i't})$

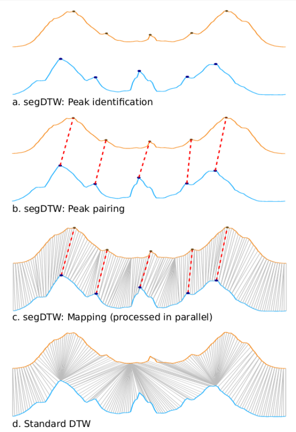
$$d(\hat{\boldsymbol{\gamma}}_i, \hat{\boldsymbol{\gamma}}_{i'}) = \min_{r \in M} \left(\sum_{t=1}^{m} |\hat{\gamma}_{it} - \hat{\gamma}_{i't}| \right).$$

- Recognise similar shapes in time series, even in the presence of shifting and/or scaling (Montero & Vilar, 2014).
- M is a set of all possible sequences of m pairs preserving the observation order in r

Clustering



Rakthanmanon et al. 2012



- Picks the deformation of the time axes of $\hat{\gamma}_i$ and $\hat{\gamma}_{i'}$ which brings the two time series as close as possible to each other

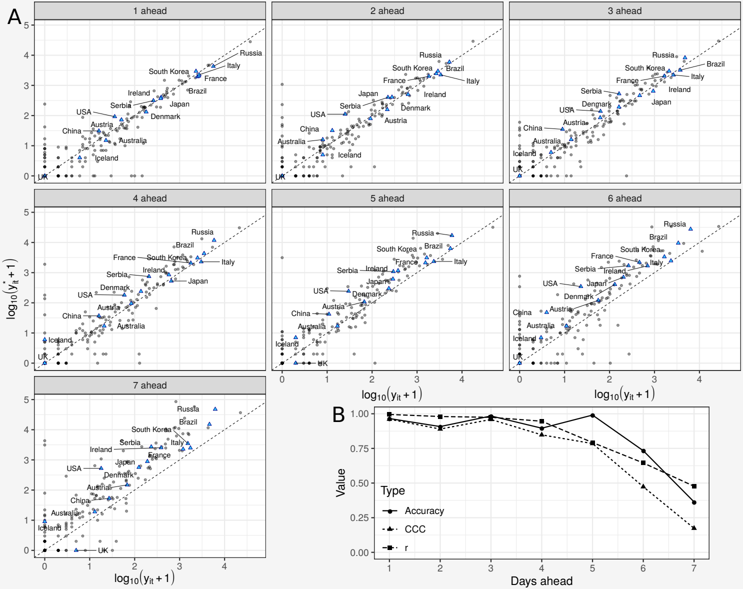
Clustering

Minimising the variability within clusters

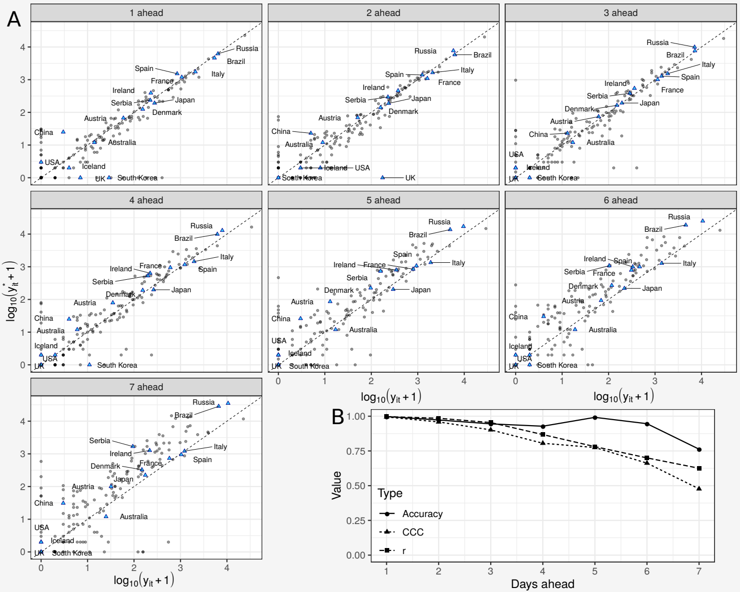
- Hierarchical clustering using the matrix of DTW distances using Ward's method (Murtagh & Legendre, 2014)
- Produce a dendrogram using hierarchical clustering analysis

Results

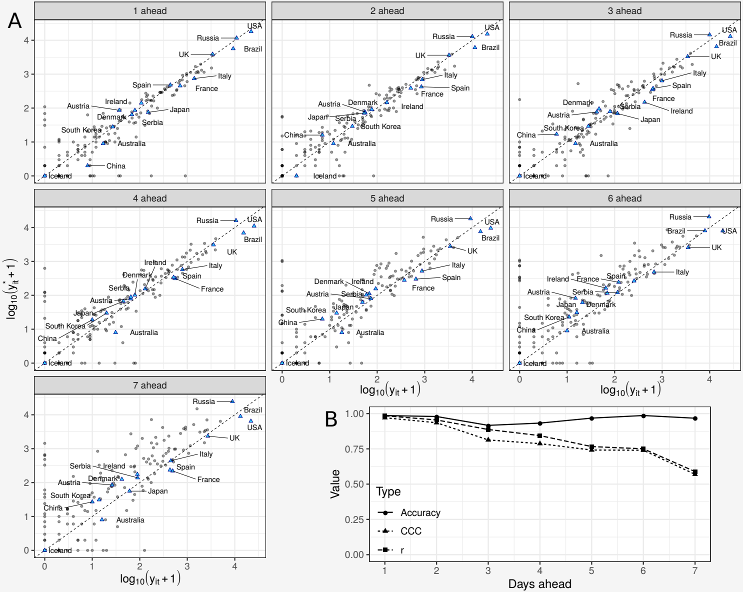
Predictive Performance - [30-April-2020, 06-May-2020]



Predictive Performance - [07-May-2020, 13-May-2020]

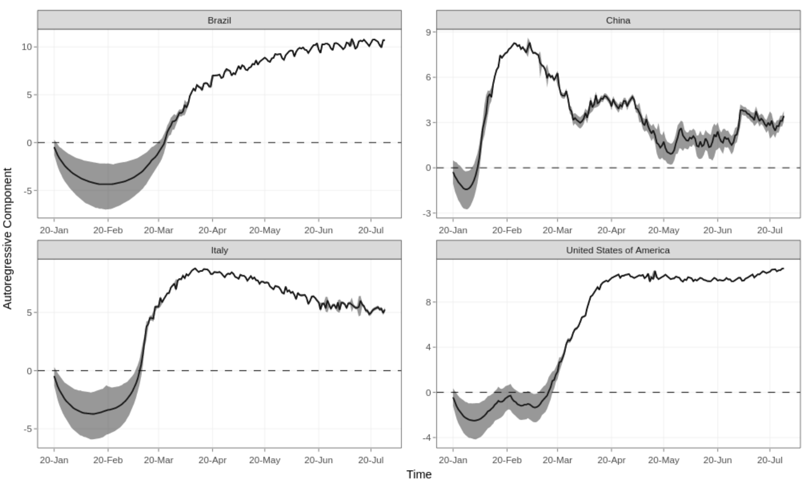


Predictive Performance - [14-May-2020, 20-May-2020]

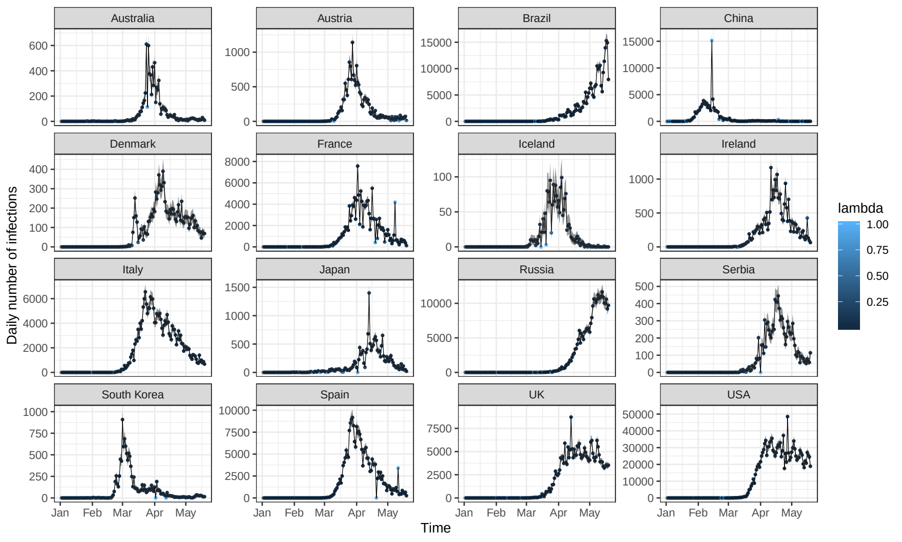


Autoregressive component - Pandemic behaviour

- Proportional to the natural logarithm of the daily number of cases
  $\gamma_{it} | \gamma_{i,t-1}$



Overdispersion Parameter $\Omega_{it} = \lambda_{it}\omega_{it}$



- large number of accumulated suspected cases that were then confirmed

Estimates

Table: Parameter estimates and associated 95% credible intervals (CI) for the fitted autoregressive hierarchical state-space negative binomial model.

Parameter	Estimate	95% CI [lower; upper]
β_0	0.9993	[0.9974, 1.0012]
β_1	−0.1658	[−0.1871, −0.1447]
β_2	0.4090	[0.3630, 0.4080]
σ_{b_0}	0.0072	[0.0061, 0.0085]
σ_{b_1}	0.0325	[0.0168, 0.0565]
σ_{b_2}	0.2392	[0.1979, 0.2821]
σ_η	0.5206	[0.5071, 0.5341]
π	0.1080	[0.0983, 0.1180]
σ_ω	3.3797	[3.1391, 3.6544]
ψ	0.0009	[0.0002, 0.0025]

- about 11% of the number of reported cases can be viewed as contributing to extra variability

Final Remarks

Final Remarks

- We introduces statistical novelty in terms of modelling the autoregressive parameter as a function of time

Final Remarks

- We introduces statistical novelty in terms of modelling the autoregressive parameter as a function of time
- Translates directly into improved predictive power in terms of forecasting future numbers of daily cases

Final Remarks

- We introduces statistical novelty in terms of modelling the autoregressive parameter as a function of time
- Translates directly into improved predictive power in terms of forecasting future numbers of daily cases
- Model can be adapted to other types of data:
  - number of deaths
  - inclusion more variable in the linear predictor
  - obtain forecasts for smaller regions within a country

Final Remarks

- We introduces statistical novelty in terms of modelling the autoregressive parameter as a function of time
- Translates directly into improved predictive power in terms of forecasting future numbers of daily cases
- Model can be adapted to other types of data:
  - number of deaths
  - inclusion more variable in the linear predictor
  - obtain forecasts for smaller regions within a country
- Model will obtain forecasts based on what is being reported
  - direct reflection of the data collection process
  - be it appropriate or not

Final Remarks

- We introduces statistical novelty in terms of modelling the autoregressive parameter as a function of time
- Translates directly into improved predictive power in terms of forecasting future numbers of daily cases
- Model can be adapted to other types of data:
  - number of deaths
  - inclusion more variable in the linear predictor
  - obtain forecasts for smaller regions within a country
- Model will obtain forecasts based on what is being reported
  - direct reflection of the data collection process
  - be it appropriate or not
- Predictive models for large countries, such as the US, are even more problematic because they aggregate heterogeneous subepidemics in local areas

References

- Holmes, E. A.et al.Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental healthscience. **The Lancet Psychiatry**, v.7, 547-560 (2020)
- Lin, L. I. A Concordance Correlation Coefficient to Evaluate Reproducibility. **Biometrics**, v. 45, 255-268 (1989)
- Muller, M. Dynamic Time Warping, v. 2, 69-84 (Springer Berlin Heidelberg, Berlin, Heidelberg, 2007).
- Montero, P. & Vilar, J. A. TSclust: An R package for time series clustering. **J. Stat. Softw**, v. 62, 1-43 (2014)
- Murtagh, F. & Legendre, P. Ward's Hierarchical Agglomerative Clustering Method: Which Algorithms Implement Ward'sCriterion? **J Classif**, v.31, 274-295 (2014)
- Rakthanmanon, T et al. Searching and Mining Trillions ofTime Series Subsequencesunder Dynamic Time Warping. **ACM**, 2012, DOI: 10.1145/2339530.2339576