Laboratoire des Sciences du Numérique de Nantes

A Scaled Poisson Bayesian Model for Viral Epidemic Monitoring

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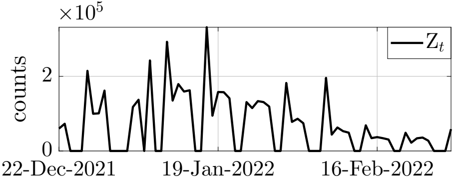
† Supported by ANR-23-CE48-0009 "*OptiMoCSI*"

Daily counts of new COVID-19 infections in Spain during 10 weeks



data collected
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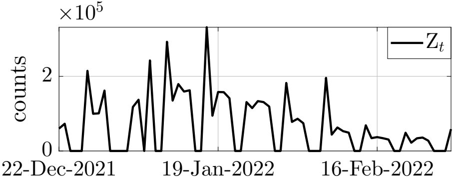

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Design and evaluation of timely and adapted sanitary control measures requires:

$\longrightarrow$ efficient monitoring tools based on sound epidemiological model,

$\longrightarrow$ robustness to low quality of the data, i.e., capacity to handle reporting errors,

$\longrightarrow$ reliable confidence levels through credibility intervals.

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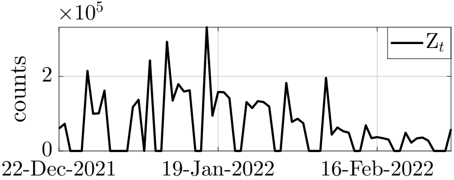

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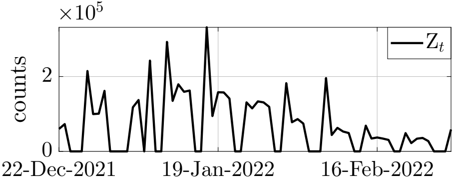
Key indicator: reproduction number R_0 (Ferguson et al., 2006, *Nature*)

"averaged number of secondary cases generated by a typical contagious individual"

$\Longrightarrow$ relaxed into an **effective time-varying reproduction number** R_t at day t

$\mathrm{R}_t > 1$: **exponential** increase of infections (Cori et al., 2013, *Am. J. Epidemiol.*)



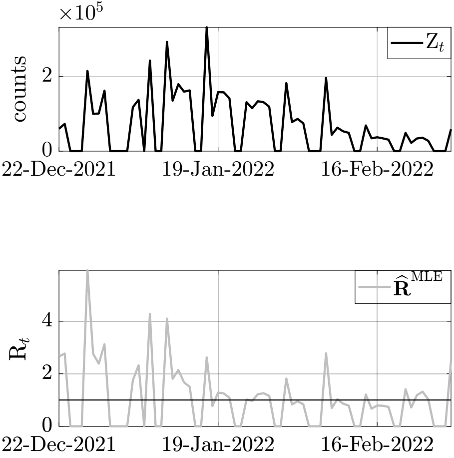
Infection counts model:

$$\mathbb{P}(Z_t | Z_{t-1}, Z_{t-2}, \ldots) = \text{Poisson}(p_t),$$

with $p_t = R_t \sum_{u=1}^{\tau} \phi_u Z_{t-u} = R_t \Phi_t$

$\{\phi_u\}_{u=1}^{\tau}$: serial interval distribution

(Cori et al., 2013, *Am. J. Epidemiol.*)



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Reference R_t estimators:

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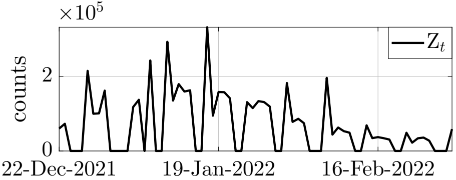

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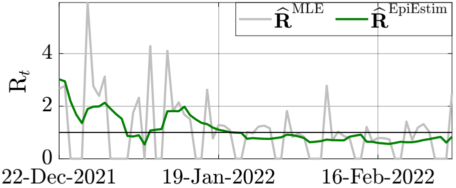

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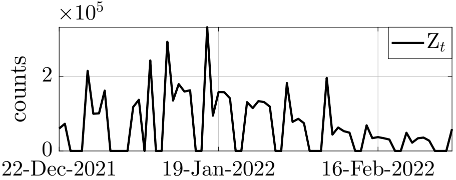
EpiEstim: $a = 1$ and $1/b = 1/5$

$$R_{t,\tau'}^{\text{EpiEstim}} := \frac{\sum_{s=t-\tau'+1}^{t} Z_s + a}{\sum_{s=t-\tau'+1}^{t} \Phi_s + 1/b}.$$

temporal smoothing over $\tau' = 7$ days



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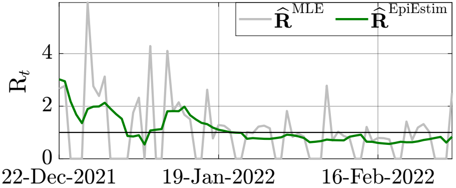

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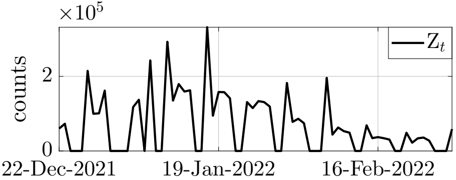

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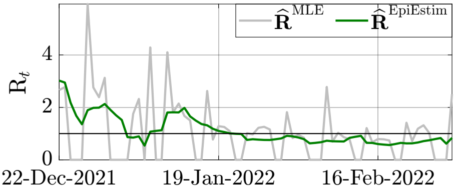

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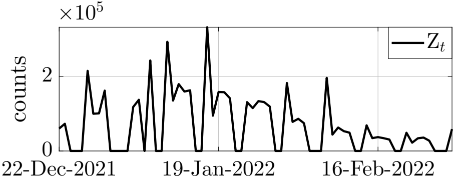
Main challenges of epidemic surveillance



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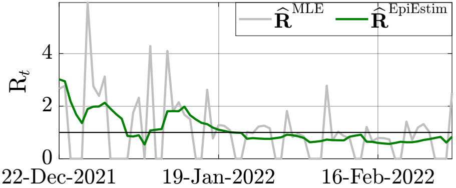

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Epidemic monitoring during T days:

- observations: $\mathbf{Z} = (Z_1, \ldots, Z_T)$ infection counts
- unknown parameters: $\mathbf{R} = (R_1, \ldots, R_T)$ time-varying reproduction number

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$$\mathbb{P}(Z_t | Z_{t-1}, Z_{t-2}, \ldots) = \text{Poisson}(\widetilde{p}_t)\,, \quad \text{with } \widetilde{p}_t = R_t \Phi_t + O_t, \quad O_t \in \mathbb{R}$$

Bayesian framework for viral epidemic modeling

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Prior distributions of unknown parameters and hidden variables:

$$(\mathrm{D}\mathbf{R})_t := (R_t - 2R_{t-1} + R_{t-2})/4 \sim \text{Laplace}(\lambda_R), \qquad O_t \sim \text{Laplace}(\lambda_O);$$

$\underline{\lambda} := (\lambda_R, \lambda_O)$: positive hyperparameters

- $R_1, \ldots, R_T$ few abrupt slope changes: temporal regularity
- $O_1, \ldots, O_T$ independent random variables: error sparsity

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$(\mathbf{Z}, \mathbf{R}, \mathbf{O})$ **log-density**: $\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) - \lambda_R \|D\mathbf{R} + \delta\| - \lambda_O \|\mathbf{O}\|$ $\quad \mathcal{I} := (\mathbf{Z}_{-\tau+1:0}, R_{-1}, R_0)$

provided that $R_t \geq 0$ and $R_t \Phi_t + O_t \geq 0$ for all t, otherwise $-\infty$;

$$\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) := \sum_{t=1}^{T} \{Z_t \ln(R_t \Phi_t + O_t) - (R_t \Phi_t + O_t)\}; \delta := ((-2R_0 + R_{-1})/4, R_0/4, 0, \cdots, 0)$$

(Fort et al., 2023, *IEEE Trans. Signal Process.*)

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Hyperparameter distribution: allow $\underline{\lambda} := (\lambda_{\mathsf{R}}, \lambda_{\mathsf{O}})$ to explore many values

product of independent **conjugate gamma** priors $\mathcal{G}\,(\alpha_{\mathsf{R}}, \beta_{\mathsf{R}}) \otimes \mathcal{G}(\alpha_{\mathsf{O}}, \beta_{\mathsf{O}})$

α_{R}, α_{O} and β_{R}, β_O shape and rate parameters respectively (Abry et al., 2025, *ICASSP*)

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Log-density of $(\mathbf{Z}, \mathbf{R}, \mathbf{O}, \underline{\lambda})$: $\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) + \mathrm{pen}(\mathbf{R}, \mathbf{O}, \underline{\lambda})$ with $\mathrm{pen}(\mathbf{R}, \mathbf{O}, \underline{\lambda}) :=$

$$-\lambda_\mathsf{R}\left(\beta_\mathsf{R} + \|\mathsf{D}\mathbf{R} + \delta\|_1\right) - \lambda_\mathsf{O}\left(\beta_\mathsf{O} + \|\mathbf{O}\|_1\right) + \left(T + \alpha_\mathsf{R} - 1\right)\ln\lambda_\mathsf{R} + \left(T + \alpha_\mathsf{O} - 1\right)\ln\lambda_\mathsf{O}$$

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Marginal distribution: $\overline{\pi}(\mathbf{R}, \mathbf{O}|\mathbf{Z}, \mathcal{I}) = \int_{\mathbb{R}_{>0}\times\mathbb{R}_{>0}} \pi(\mathbf{R}, \mathbf{O}, \underline{\lambda}|\mathbf{Z}, \mathcal{I})\mathrm{d}\underline{\lambda}$

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with $\exp(\overline{\mathrm{pen}}(\mathbf{R}, \mathbf{O})) \propto \left(\beta_{\mathsf{R}} + \|\mathsf{D}\mathbf{R} + \delta\|_1\right)^{-(T+\alpha_{\mathsf{R}})}\left(\beta_{\mathsf{O}} + \|\mathbf{O}\|_1\right)^{-(T+\alpha_{\mathsf{O}})}$

COVID-19 pandemic propagation hierarchical model

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Gibbs sampler: Markov chain Monte Carlo algorithm targeting $\overline{\pi}$

- Adjusted Proximal-Langevin mechanism `PGdual` to sample $\mathbf{R}, \mathbf{O}|\underline{\lambda}$
- Exact conditional sampling of $\underline{\lambda}|\mathbf{R}, \mathbf{O}$ thanks to conjugate priors

(Fort et al., 2023, *IEEE Trans. Signal Process.; Abry et al., 2025, ICASSP*)

Hierarchical **estimates:** $k_{\max} = 5 \cdot 10^7$ including $k_{\text{burn-in}} = 3 \cdot 10^7$ iterations

$$\widehat{\mathbf{R}}^{\text{Hierarchical}} := \frac{1}{K} \sum_{k=k_{\text{burn-in}}}^{k_{\max}} \mathbf{R}^{(k)}, \quad \mathbf{Z} - \widehat{\mathbf{O}}^{\text{Hierarchical}} := \mathbf{Z} - \frac{1}{K} \sum_{k=k_{\text{burn-in}}}^{k_{\max}} \mathbf{O}^{(k)}$$

and 95% **credibility intervals** from 2.5% and 97.5% empirical quantiles

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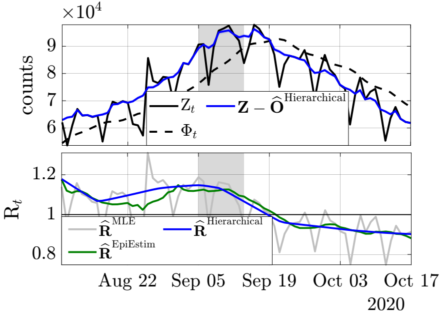
Daily surveillance of COVID-19 pandemic in India during 10 weeks



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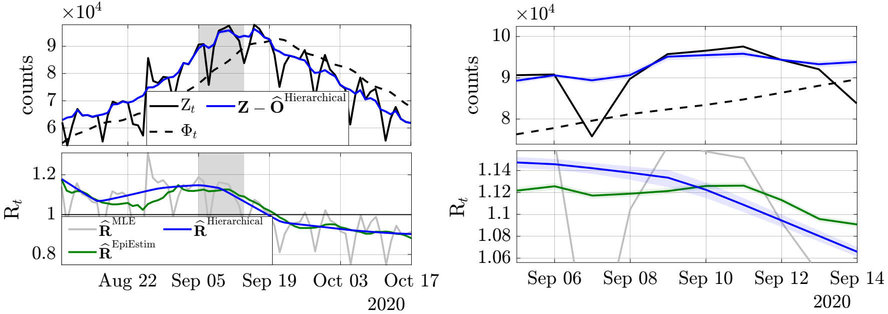

accurate mean a posteriori estimates but **unrealistically narrow** credibility interval

Scaled-likelihood accounting for model misspecification

Tempered likelihood:

$$\overline{\pi}_{\nu}(\mathbf{R}, \mathbf{O}|\mathbf{Z}, \mathcal{I}) \propto \exp\left(\frac{1}{\nu}\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) + \overline{\mathrm{pen}}(\mathbf{R}, \mathbf{O})\right)$$

$\Longrightarrow$ unbalances likelihood vs. priors

- $\nu = 1$ standard Poisson
- $\nu = \infty$ prior distribution
- $\nu > 1$ count **over-dispersion**

In practice: $\nu \propto \mathrm{std}(\mathbf{Z})$

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Markov Chain Monte Carlo algorithm:

Input: $\mathbf{Z}, \Phi, \mathcal{I}, \nu$;
Parameters: $(\alpha_{\mathrm{R}}, \beta_{\mathrm{R}}, \alpha_{\mathrm{O}}, \beta_{\mathrm{O}})$, $k_{\max}$;
Initialize: $(\mathbf{R}^{(0)}, \mathbf{O}^{(0)}, \underline{\lambda}^{(0)})$;
for $k = 0, 1, \ldots, k_{\max} - 1$ **do**
 # Sample $\mathbf{R}$ *then* $\mathbf{O}$ *at fixed* $\lambda_{\mathrm{R}}^{(k)}, \lambda_{\mathrm{O}}^{(k)}$
 $\mathbf{R}^{(k+1)}, \mathbf{O}^{(k+1)} \sim \nu\text{-}\texttt{PGdual}(\mathbf{R}^{(k)}, \mathbf{O}^{(k)}; \lambda_{\mathrm{R}}^{(k)}, \lambda_{\mathrm{O}}^{(k)})$;
 # Sample λ_{R} *then* λ_{O} *at fixed* $\mathbf{R}^{(k+1)}, \mathbf{O}^{(k+1)}$
 $\lambda_{\mathrm{R}}^{(k+1)} \sim \mathcal{G}(T + \alpha_{\mathrm{R}}, \|\mathrm{D}\mathbf{R}^{(k+1)} + \delta\| + \beta_{\mathrm{R}})$;
 $\lambda_{\mathrm{O}}^{(k+1)} \sim \mathcal{G}(T + \alpha_{\mathrm{O}}, \|\mathbf{O}^{(k+1)}\| + \beta_{\mathrm{O}})$;
end for
Output: $\{\mathbf{R}^{(k)}, \mathbf{O}^{(k)}, \lambda_{\mathrm{R}}^{(k)}, \lambda_{\mathrm{O}}^{(k)}\}_{k=1,\ldots,k_{\max}}$

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Markov Chain Monte Carlo algorithm:

Input: $\mathbf{Z}, \Phi, \mathcal{I}, \nu$;
Parameters: $(\alpha_\mathrm{R}, \beta_\mathrm{R}, \alpha_\mathrm{O}, \beta_\mathrm{O})$, k_max;
Initialize: $(\mathbf{R}^{(0)}, \mathbf{O}^{(0)}, \underline{\lambda}^{(0)})$;
for $k = 0, 1, \ldots, k_\mathrm{max} - 1$ **do**
  # Sample **R** *then* **O** *at fixed* $\lambda_\mathrm{R}^{(k)}, \lambda_\mathrm{O}^{(k)}$
  $\mathbf{R}^{(k+1)}, \mathbf{O}^{(k+1)} \sim \nu\text{-}\mathtt{PGdual}(\mathbf{R}^{(k)}, \mathbf{O}^{(k)}; \lambda_\mathrm{R}^{(k)}, \lambda_\mathrm{O}^{(k)})$;
  # Sample λ_R *then* λ_O *at fixed* $\mathbf{R}^{(k+1)}, \mathbf{O}^{(k+1)}$
  $\lambda_\mathrm{R}^{(k+1)} \sim \mathcal{G}(T + \alpha_\mathrm{R}, \|\mathrm{D}\mathbf{R}^{(k+1)} + \delta\| + \beta_\mathrm{R})$;
  $\lambda_\mathrm{O}^{(k+1)} \sim \mathcal{G}(T + \alpha_\mathrm{O}, \|\mathbf{O}^{(k+1)}\| + \beta_\mathrm{O})$;
end for
Output: $\{\mathbf{R}^{(k)}, \mathbf{O}^{(k)}, \lambda_\mathrm{R}^{(k)}, \lambda_\mathrm{O}^{(k)}\}_{k=1,\ldots,k_\mathrm{max}}$

Proposed ν-scaled **estimates:** $k_\mathrm{max} = 5 \cdot 10^7$ including $k_\text{burn-in} = 3 \cdot 10^7$ iterations

$$\widehat{\mathbf{R}}^{\nu\text{-scaled}} := \frac{1}{K}\sum_{k=k_\text{burn-in}}^{k_\mathrm{max}} \mathbf{R}^{(k)}, \quad \mathbf{Z} - \widehat{\mathbf{O}}^{\nu\text{-scaled}} := \mathbf{Z} - \frac{1}{K}\sum_{k=k_\text{burn-in}}^{k_\mathrm{max}} \mathbf{O}^{(k)}$$

and 95% **credibility intervals** from 2.5% and 97.5% empirical quantiles

Log-density of $(\mathbf{Z}, \mathbf{R}, \mathbf{O}, \underline{\lambda})$: $\nu^{-1}\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) + \mathrm{pen}(\mathbf{R}, \mathbf{O}, \underline{\lambda})$ with $\mathrm{pen}(\mathbf{R}, \mathbf{O}, \underline{\lambda}) :=$

$$-\lambda_\mathsf{R}\,(\beta_\mathsf{R} + \|\mathsf{D}\mathbf{R} + \delta\|_1) - \lambda_\mathsf{O}\,(\beta_\mathsf{O} + \|\mathbf{O}\|_1) + (T + \alpha_\mathsf{R} - 1)\ln\lambda_\mathsf{R} + (T + \alpha_\mathsf{O} - 1)\ln\lambda_\mathsf{O}$$

including conjugate gamma priors on $\underline{\lambda} = (\lambda_\mathsf{R}, \lambda_\mathsf{O}) \sim \mathcal{G}\,(\alpha_\mathsf{R}, \beta_\mathsf{R}) \otimes \mathcal{G}(\alpha_\mathsf{O}, \beta_\mathsf{O})$

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Scaled marginal distribution: $\ln\overline{\pi}_\nu(\mathbf{R}, \mathbf{O}|\mathbf{Z}, \mathcal{I}) = \nu^{-1}\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) + \overline{\mathrm{pen}}(\mathbf{R}, \mathbf{O})$ with

$$\exp(\overline{\mathrm{pen}}(\mathbf{R}, \mathbf{O})) \propto \left(\beta_{\mathsf{R}} + \|\mathsf{D}\mathbf{R} + \delta\|_1\right)^{-(T+\alpha_{\mathsf{R}})}\left(\beta_{\mathsf{O}} + \|\mathbf{O}\|_1\right)^{-(T+\alpha_{\mathsf{O}})}$$

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Quasi-noninformative priors on $\underline{\lambda} = (\lambda_{\mathsf{R}}, \lambda_{\mathsf{O}})$: gamma distributions

- means $\alpha_{\mathsf{R}}/\beta_{\mathsf{R}} = 3.5 \times \mathrm{std}(\mathbf{Z})$
  $\alpha_{\mathsf{O}}/\beta_{\mathsf{O}} = 5 \times 10^{-2}$

(Pascal et al., 2022, IEEE Trans. Signal Process)

Log-density of $(\mathbf{Z}, \mathbf{R}, \mathbf{O}, \underline{\lambda})$: $\nu^{-1}\ell(\mathbf{Z}|\mathbf{R}, \mathbf{O}, \mathcal{I}) + \mathrm{pen}(\mathbf{R}, \mathbf{O}, \underline{\lambda})$ with $\mathrm{pen}(\mathbf{R}, \mathbf{O}, \underline{\lambda}) :=$

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$$\exp(\overline{\mathrm{pen}}(\mathbf{R}, \mathbf{O})) \propto \left(\beta_{\mathsf{R}} + \|\mathsf{D}\mathbf{R} + \delta\|_1\right)^{-(T+\alpha_{\mathsf{R}})}\left(\beta_{\mathsf{O}} + \|\mathbf{O}\|_1\right)^{-(T+\alpha_{\mathsf{O}})}$$

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- means $\alpha_{\mathsf{R}}/\beta_{\mathsf{R}} = 3.5 \times \mathrm{std}(\mathbf{Z})$
  $\alpha_{\mathsf{O}}/\beta_{\mathsf{O}} = 5 \times 10^{-2}$ (Pascal et al., 2022, IEEE Trans. Signal Process)
- standard deviations $\sqrt{\alpha_{\mathsf{R}}}/\beta_{\mathsf{R}} = 50 \times (\alpha_{\mathsf{R}}/\beta_{\mathsf{R}})$, $\sqrt{\alpha_{\mathsf{O}}}/\beta_{\mathsf{O}} = 80 \times (\alpha_{\mathsf{O}}/\beta_{\mathsf{O}})$

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Quasi-noninformative priors on $\underline{\lambda} = (\lambda_\mathrm{R}, \lambda_\mathrm{O})$: gamma distributions

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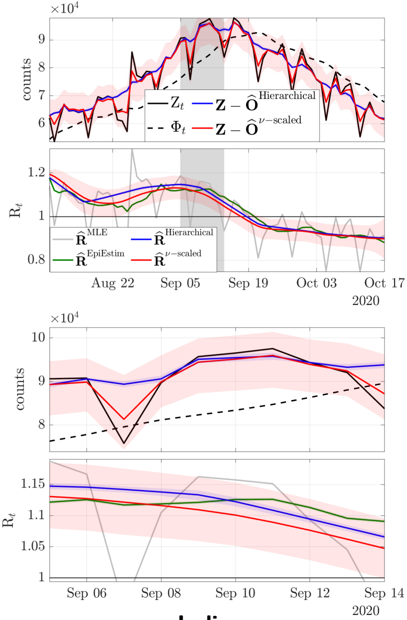
- standard deviations $\sqrt{\alpha_\mathrm{R}}/\beta_\mathrm{R} = 50 \times (\alpha_\mathrm{R}/\beta_\mathrm{R})$, $\sqrt{\alpha_\mathrm{O}}/\beta_\mathrm{O} = 80 \times (\alpha_\mathrm{O}/\beta_\mathrm{O})$

Hierarchical **estimator**, i.e., $\nu = 1$: informative gamma priors on $\underline{\lambda}$

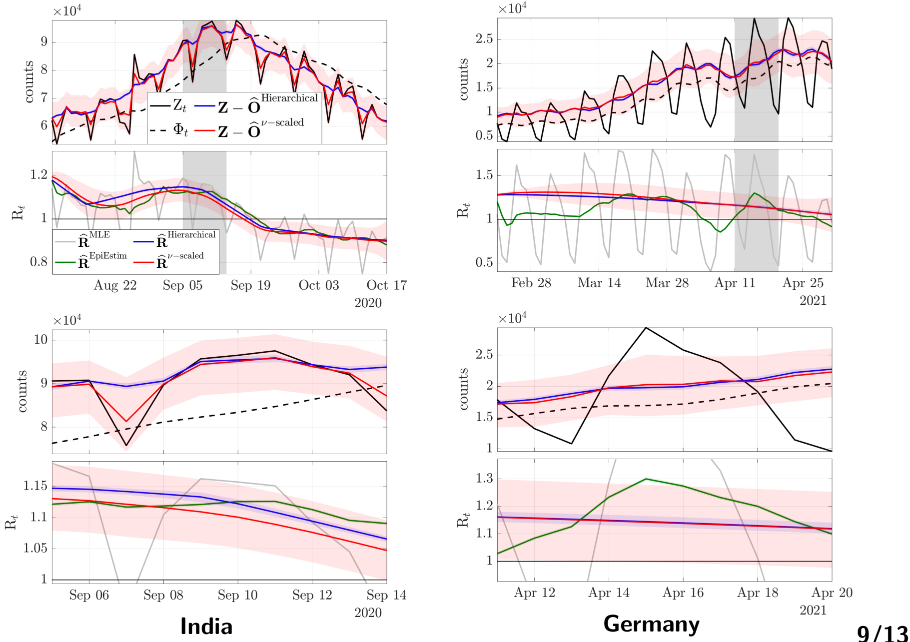
- means $\alpha_\mathrm{R}/\beta_\mathrm{R} = 3.5 \times \mathrm{std}(\mathbf{Z})$
  $\alpha_\mathrm{O}/\beta_\mathrm{O} = 5 \times 10^{-2}$ (Pascal et al., 2022, IEEE Trans. Signal Process)
- standard deviations $\sqrt{\alpha_\mathrm{R}}/\beta_\mathrm{R} = 0.02 \times (\alpha_\mathrm{R}/\beta_\mathrm{R})$, $\sqrt{\alpha_\mathrm{O}}/\beta_\mathrm{O} = 0.0125 \times (\alpha_\mathrm{O}/\beta_\mathrm{O})$
  (Abry et al., 2025, ICASSP)

Robust estimation of reproduction number credibility intervals



India

Robust estimation of reproduction number credibility intervals



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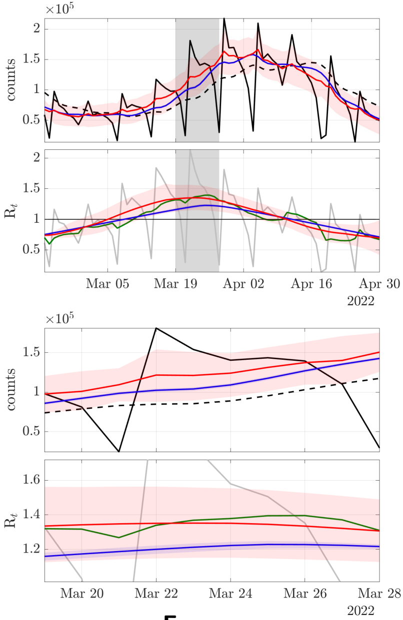
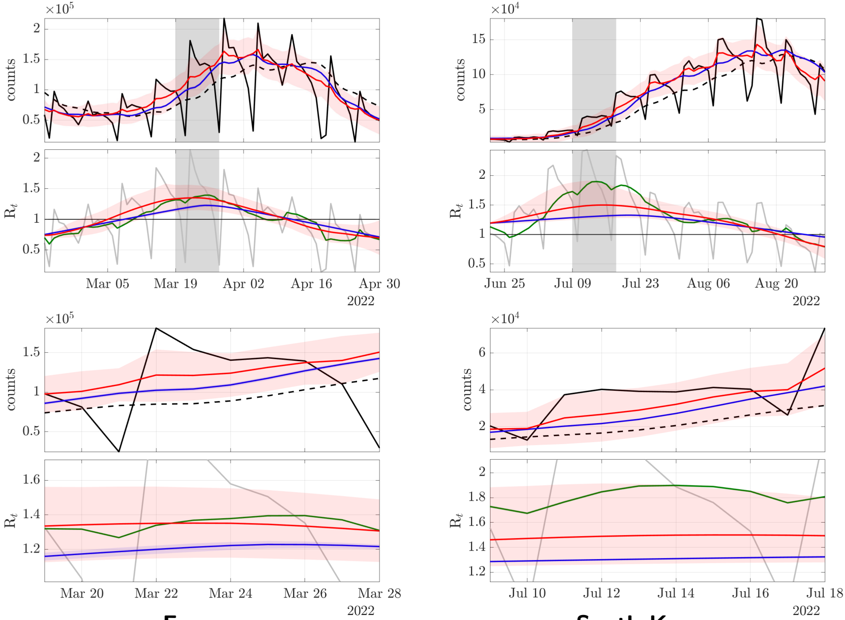


France

Robust estimation of reproduction number credibility intervals



France **South Korea**

Absolute value of autocorrelation averaged across the T components:

- $\mathsf{R}_t^{(0)} = (\mathsf{R}_{t,7}^{\mathsf{EpiEstim}} + 1)/2, \quad \mathsf{O}_t^{(0)} = (\mathsf{Z}_t - \mathsf{R}_{t,7}^{\mathsf{EpiEstim}} \Phi_t)/2$
- $\lambda_{\mathsf{R}}^{(0)} = \alpha_{\mathsf{R}}/\beta_{\mathsf{R}}$
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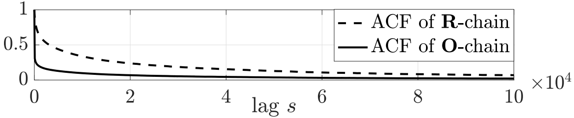

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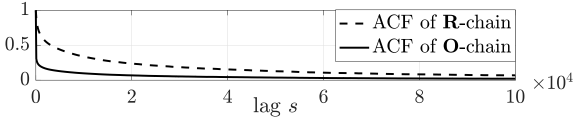

Area covered by reproduction number credibility intervals

- averaged over **10 runs** of the Gibbs sampler
- accompanied with 95% Gaussian confidence intervals

	India	Germany	France	South Korea
EpiEstim (Cori et al., 2013, Am. J. Epidemiol.)	0.4	1.1	0.4	0.8
Hierarchical (Abry et al., 2025, ICASSP)	$0.6 \pm 0.0^*$	$2.1 \pm 0.0^*$	1.4 ± 0.1	$0.9 \pm 0.0^*$
ν-scaled				
$\nu = 0.025 \times \mathrm{std}(\mathbf{Z})$	7.6 ± 0.1	18.3 ± 0.2	22.6 ± 0.4	22.6 ± 1.0

* 95% confidence intervals smaller than 0.1

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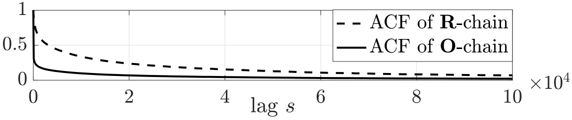

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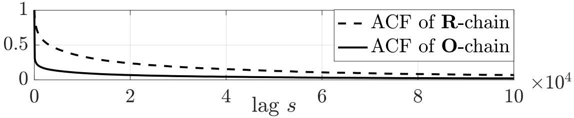

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$\nu = 0.025 \times \text{std}(\mathbf{Z})$	7.6 ± 0.1	18.3 ± 0.2	22.6 ± 0.4	22.6 ± 1.0
$\nu = 0.05 \times \text{std}(\mathbf{Z})$	8.2 ± 0.1	19.0 ± 0.6	23.4 ± 0.6	22.6 ± 0.8

* 95% confidence intervals smaller than 0.1

Contributions and take home messages

- Bayesian modeling of epidemic propagation accounting for **low quality** counts
- Introduction of a **scale** parameter ν to account for count **over-dispersion**
- Efficient original **Gibbs** sampler adapted to the **hierarchical** model
- Uncertainty quantification through estimation of **credibility intervals**
- **Robustness** of the estimates to model misspecification

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Accurate estimates and **trustworthy** credibility intervals $\Longrightarrow$ **usable by nonspecialists**

- improvement in accuracy compared to reference methods
- more realistic credibility intervals than previously designed Bayesian estimates
- quantified convergence of the MCMC algorithm and robustness to choice of ν

Matlab toolbox publicly available at github.com/gfort-lab/OpSiMorE

Future work and perspectives

- Decoupling of the stochastic **pathogen propagation** and **administrative noise**

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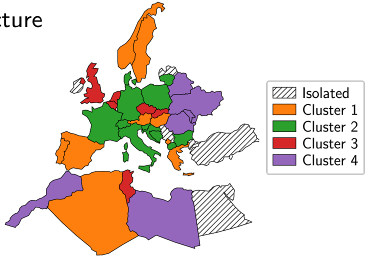
- **Spatiotemporal** pandemic monitoring

Future work and perspectives

- Decoupling of the stochastic **pathogen propagation** and **administrative noise**
- **Spatiotemporal** pandemic monitoring: for the moment
  - pointwise estimates, not yet uncertainty quantifications
  - data-driven inference of the spatial structure



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Track	Statistical signal processing [TM-SSP]
Session	SPTM-P19: Distributed Optimization II — Poster
Presentation Time	Fri, 8 May, 14:00 - 16:00 Spain Time (UTC +2)
Authors	Etienne Lasalle, Barbara Pascal, Nantes Université, Ecole Centrale Nantes, CNRS, France

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