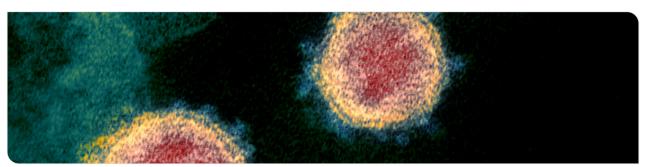


Collaborative nowcasting of COVID-19 hospitalization incidences

DAGStat

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Contributors

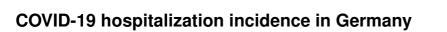


This is joint work with

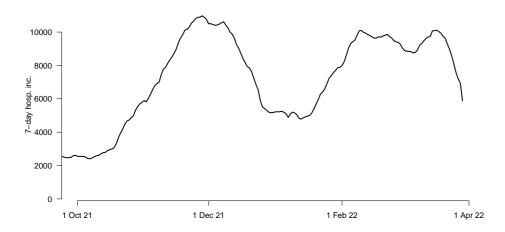
- Daniel Wolffram, Davide Hailer, Tilmann Gneiting, Melanie Schienle (KIT/HITS)
- Helmut Küchenhoff, Diella Syliqi, Maximilan Weigert (LMU Munich)
- Sam Abbott, Sebastian Funk (London School of Hygiene and Tropical Medicine)
- Jan van de Kassteele (RIVM Bilthoven)
- Matthias an der Heiden, Alexander Ullrich (Robert Koch Institut)
- Stefan Heyder, Thomas Hotz (TU Ilmenau)
- Felix Günther (University of Stockholm)

with contributions by

Sören Müller-Hansen (Süddeutsche Zeitung)

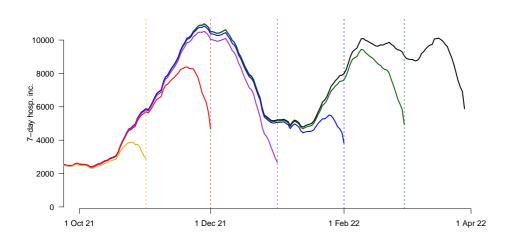












Seven day hospitalization incidence

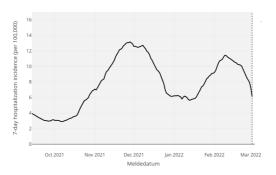


- **Definition:** The number of persons, who over a seven-day period
 - have been registered electronically as a COVID-19 case by a local health authority (Meldedatum).
 - and have been hospitalized (not necessarily during the seven-day period).
- This is **not** the number of new hospitalizations over the last seven days.
- This number does not take into account whether COVID-19 was the reason of hospitalization.
- Most recent values are biased downwards due to two types of delays:
 - delay between *Meldedatum* (\approx positive test) and hospitalization.
 - delay between hospitalization and appearance in RKI data.





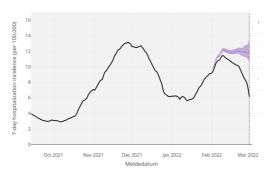
- Goal: Estimate (predict) what preliminary/incomplete values will ultimately look like.
 - Stratified for states and age groups.
 - In real time.
- In a way this is a forecast rather than a nowcast: some hospitalizations in question have not yet happened.



Nowcasting aims to correct the reporting dip



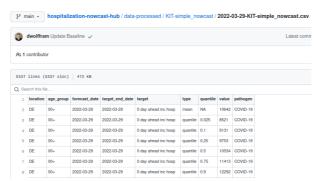
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Multi-model nowcasting



- Experience from e.g., weather forecasting shows that combining different models can improve predictions.
- We collect and combine probabilistic nowcasts from 8 independently run models.
- Daily subimssions to a public GitHub repository:

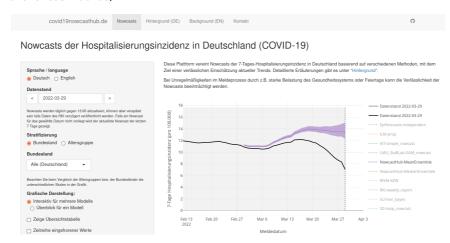


https://github.com/KITmetricslab/hospitalization-nowcast-hub/tree/main/data-truth/COVID-19





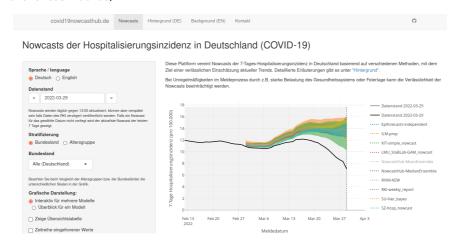
https://covid19nowcasthub.de/







https://covid19nowcasthub.de/





The statistical problem: completing the reporting triangle

Example with maximum reporting delay of 5 days. On day t^* , the black cells are known, the blue cells need to be estimated.

| day | d = 0 | d = 1 | d=2 | d = 3 | d = 4 | d = 5 | total |
|-----------|-------------------------|-------------------------|------------------|-------------------------|------------------|-------------------------|-----------------------|
| 1 | <i>x</i> _{1,0} | x _{1,1} | x _{1,2} | <i>x</i> _{1,3} | X _{1,4} | x _{1,5} | <i>X</i> ₁ |
| 2 | <i>X</i> _{2,0} | <i>X</i> _{2,1} | X _{2,2} | X _{2,3} | X _{2,4} | <i>x</i> _{2,5} | <i>X</i> ₂ |
| : | | | | | | | |
| - | | | | | | | |
| $t^* - 5$ | $x_{t^*-5,0}$ | $X_{t^*} = 5,1$ | $x_{t^*-5,2}$ | $x_{t^*-5,3}$ | $x_{t^*-5,4}$ | $x_{t^*-5,5}$ | $X_{t^*}_{-5}$ |
| $t^* - 4$ | $x_{t^*-4,0}$ | $x_{t^*-4,1} <$ | $x_{t^*-4,2}$ | $x_{t^*-4,3}$ | $x_{t^*-4,4}$ | $x_{t^*-4,4}$ | x_{t^*-4} |
| $t^* - 3$ | $x_{t^*-3,0}$ | $x_{t^*-3,1}$ | $x_{t^*-3,2}$ | $x_{t^*-3,3}$ | $x_{t^*-3,4}$ | $x_{t^*-3,5}$ | x_{t^*-3} |
| $t^* - 2$ | $X_{t^*} = 2,0$ | X_{t^*} -2,1 | $X_{t^*-2,2}$ | $X_{t^*-2,3}$ | $X_{t^*-2,4}$ | $x_{t^*-2,5}$ | x_{t^*-2} |
| $t^* - 1$ | $X_{t^*-1,0}$ | $X_{t^*-1,1}$ | $X_{t^*-1,2}$ | $X_{t^*-1,3}$ | $X_{t^*-1,4}$ | $x_{t^*-1,5}$ | x_{t^*-1} |
| t* | $x_{t^*,0}$ | $x_{t^*,1}$ | $x_{t^*,2}$ | $x_{t^*,3}$ | $X_{t^*,4}$ | $x_{t^*,5}$ | x_{t^*} |

Approaches taken by different teams



Three main sources of information on unknown values:

- incomplete hospitalization numbers for same day
- incomplete hospitalization numbers from surrounding days
- case numbers

Strategies to extrapolate the reporting triangle:

- Multiplication factors (KIT, RKI, SZ)
- Regression with splines for smooth time trends (RIVM Bilthoven, LMU Munich) •
- Random walk / autoregression and parametric delay distributions (LSHTM, Stockholm University)
- Regression on case incidences (TU Ilmenau)

Additional difficulties

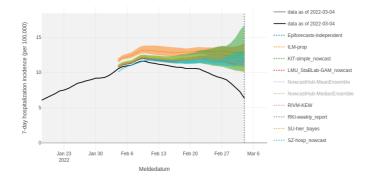


- Two types of within-week seasonality need to be taken into account:
 - seasonality in reporting of cases
 - seasonality in reporting of hospitalizations
- Delay patterns change over time, so choosing an appropriate data subset for trainint is important.
- Occasional major reporting issues can mess up things.

The ensemble



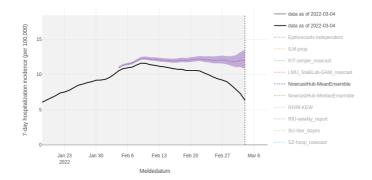
- The main output of the platform is an ensemble nowcast, i.e. combination of all available models.
- It is obtained as a simple quantile-wise mean (or median) of the different submissions.
- Intuition: We hope that similarly many models will be off upwards and downwards.



The ensemble

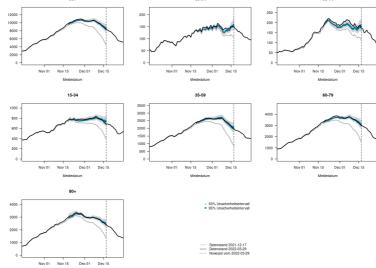


- The main output of the platform is an **ensemble nowcast**, i.e. combination of all available models.
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Nowcasts and later observed data nicely agree...



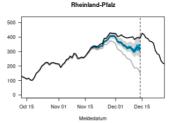




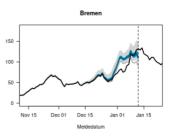
Saxony, 23 Nov 21



Rheinland-Pfalz, 14 Dec 21



Bremen 12 Jan 22







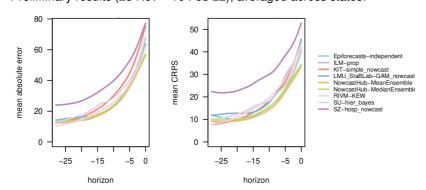
- We are conducting a systematic evaluation study of real-time nowcasts from different methods.
- This study has been pre-registered (https://osf.io/mru75/) and runs from Nov 2021 through Apr 2022.





Preliminary evaluation of point and probabilistic nowcasts

We use absolute errors and (approximate) CRPS to evaluate nowcasts probabilistically (lower is better). Preliminary results (23 Nov – 10 Feb 22), averaged across states:



For reference: average observed value on the absolute scale is \sim 500.

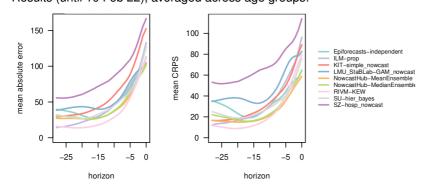
See also real-time evaluation by Sam Abbott:

https://epiforecasts.io/eval-germany-sp-nowcasting/real-time-method-comparison/



Preliminary evaluation of point and probabilistic nowcasts

We use absolute errors and (approximate) CRPS to evaluate nowcasts probabilistically (lower is better). Results (until 10 Feb 22), averaged across age groups:



For reference: average observed value on the absolute scale is \sim 1300.

See also real-time evaluation by Sam Abbott:

https://epiforecasts.io/eval-germany-sp-nowcasting/real-time-method-comparison/

Takeaways

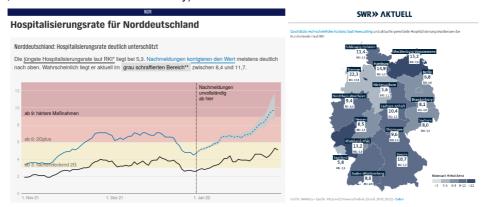


- In most cases, nowcasts have conveyed a good picture of actual trends.
- Most methods, however, have issued somewhat overconfident uncertainty intervals.
- In some instances (e.g., in Saxony in November), nowcasts have been strongly off. Sometimes we manage to warn users in these cases, sometimes this is hard to anticipate.
- Ensemble nowcasts improve somewhat, but not drastically upon individual models.
- Collaborative work is rewarding and instructive.

Dissemination



 The nowcasts have been used by numerous media outlets (Die Zeit, Süddeutsche Zeitung, Der Spiegel, Focus, Science Media Center Germany)



Thanks a lot to all contributors!

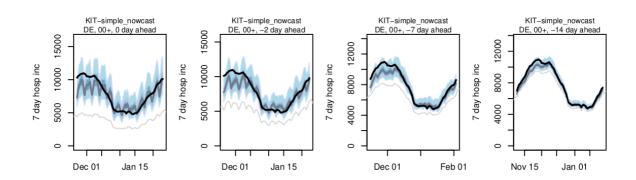
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- England and Verrall (2002): Stochastic Claims Reserving in General Insurance. British Actuarial Journal 8(3): 443 – 518.
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 Biometrical Journal 63(3): 490–502.
- Höhle and an der Heiden (2014): Bayesian nowcasting during the STEC O104:H4 outbreak in Germany, 2011. Biometrics 70(4): 993–1002.
- Schneble, De Nicola, Kauermann, Berger (2021): Nowcasting fatal COVID-19 infections on a regional level in Germany. Biometrical Journal 63(3): 471–489 U Schneble, M, De Nicola, G, Kauermann, G, Berger
- van de Kassteele, Eilers and Wallinga (2019): Nowcasting the Number of New Symptomatic Cases During Infectious Disease Outbreaks Using Constrained P-spline Smoothing. Epidemiology 30(5): 737–745.

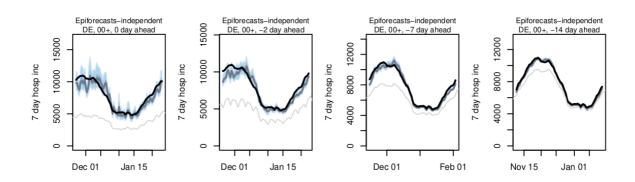
How well do the nowcasts work? (2)





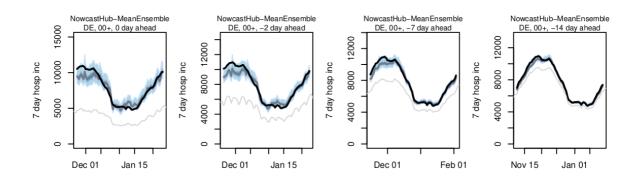
How well do the nowcasts work? (2)





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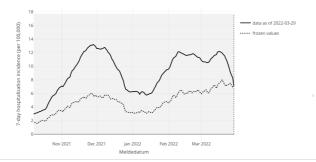






Official thresholds are based on frozen values:

- For each date use value as of that same date, without any retrospective completion
- lacktriangle All values are then "similarly incomplete" o trends interpretable
- Downsides:
 - reporting delays vary across Bundesländer
 - strong within-week seasonality



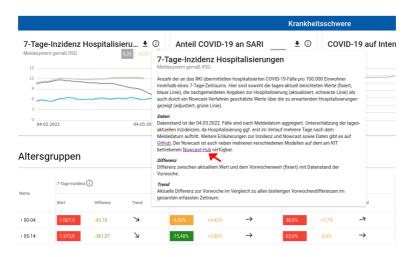
Corrected hospitalization incidences by Robert Koch Institute



Altersgruppen



Corrected hospitalization incidences by Robert Koch Institute







Three simple steps (similar to e.g. England and Verrall 2002):

• Fill in missing entries of reporting triangle using simple multiplication scheme:

| | • | | | • | | | | | |
|--|-------------------------|------------------|------------------|------------------|-----------------------|--|--|--|--|
| day | d = 0 | d = 1 | d=2 | d = 3 | total | | | | |
| 1 | <i>x</i> _{1,0} | X _{1,1} | X _{1,2} | X _{1,3} | <i>x</i> ₁ | | | | |
| 2 | <i>x</i> _{2,0} | <i>X</i> 2,1 | X2,2 | <i>X</i> 2,3 | <i>X</i> ₂ | | | | |
| : | | | | | | | | | |
| : | | | | | | | | | |
| t^*-2 | $x_{t^*-2,0}$ | $x_{t^*-2,1}$ | $x_{t^*-2,2}$ | $x_{t^*-2,3}$ | x_{t^*-2} | | | | |
| t^* – : | 1 $x_{t^*-1,0}$ | $X_{t^*-1,1}$ | $x_{t^*-1,2}$ | $X_{t^*-1,3}$ | x_{t^*-1} | | | | |
| t* | $x_{t^*,0}$ | $x_{t^*,1}$ | $x_{t^*,2}$ | $x_{t^*,3}$ | x_{t^*} | | | | |
| E.g., $X_{t^*,1} = \frac{\sum_{i=1}^{t^*-1} x_{t^*-i,1}}{\sum_{i=1}^{t^*-1} x_{t^*-i,0}} \times X_{t^*,0}$ | | | | | | | | | |

- Compute the same "estimates" for past time points, using data available up to the respective day.
- Obtain prediction intervals from past nowcast errors. This is actually more tricky than it sounds.





Nowcasting - Bayesian hierarchical model

Notation

Main assumptions: (1) hospitalization curve is somewhat "smooth"
(2) delay patterns between infection and hospitalization constant

No assumptions on time-constant case hospitalization rate.

• $\lambda_{t,s}$: expected number of hospitalizations in strata s with infection registration at day $t = 0, \dots, T$

• $p_{t,d,s}$: probability of individual (from group s) with registration at day t to be reported as hospitalized with delay d = 0, ..., D (of all individuals that will become hospitalized) delay distribution is modelled in a parametric fashion

Bayesian hierarchical model

Building up on Höhle [1], McGough [2], and Günther [3]

Latent random walk

governing the overall
hospitalization curve
(= smoothness assumpt.)

$$\log(\lambda_{t,s})|\lambda_{t-1,s} \sim N(\log(\lambda_{t-1,s}) + \beta_{wd(t)}, \sigma_s^2)$$

$$n_{t,d,s}|\lambda_{t,s}, p_{t,d,s} \stackrel{iid}{\sim} NB(\lambda_{t,s} \cdot p_{t,d,s}, \phi_s)$$

- $n_{t,d,s}$: observed data for all $t + d \le T$
- $\cdot p_{t,d}$ modelled discrete time hazard model

Hospitalizations with different delays modelled depending on delay distribution and latent random walk