COVID-19 ForecastHub

COVID-19 Forecast Hub

Jarad Niemi

15 Oct 2020

covid19forecasthub.org
jarad.me

COVID-19 Forecast Hub Team

Team: Nutcha Wattanachit, Serena Wang, Nicholas Reich, Evan Ray, Jarad Niemi, Khoa Le, Abdul Hannan Kanji, Yuxin “David” Huang, Katie House, Estee Cramer, Matt Cornell, Andrea Brennen, Johannes Bracher

* underline denotes ensemble contributor

CDC Collaborators: Michael Johansson, Matthew Biggerstaff, Joseph Walker, Velma Lopez, Rachel Slayton

Ensemble "advisory committee": Sebastian Funk, Tilmann Gneiting, Anja Muhlemann, Ryan Tibshirani

COVID-19 Forecast Hub Timeline

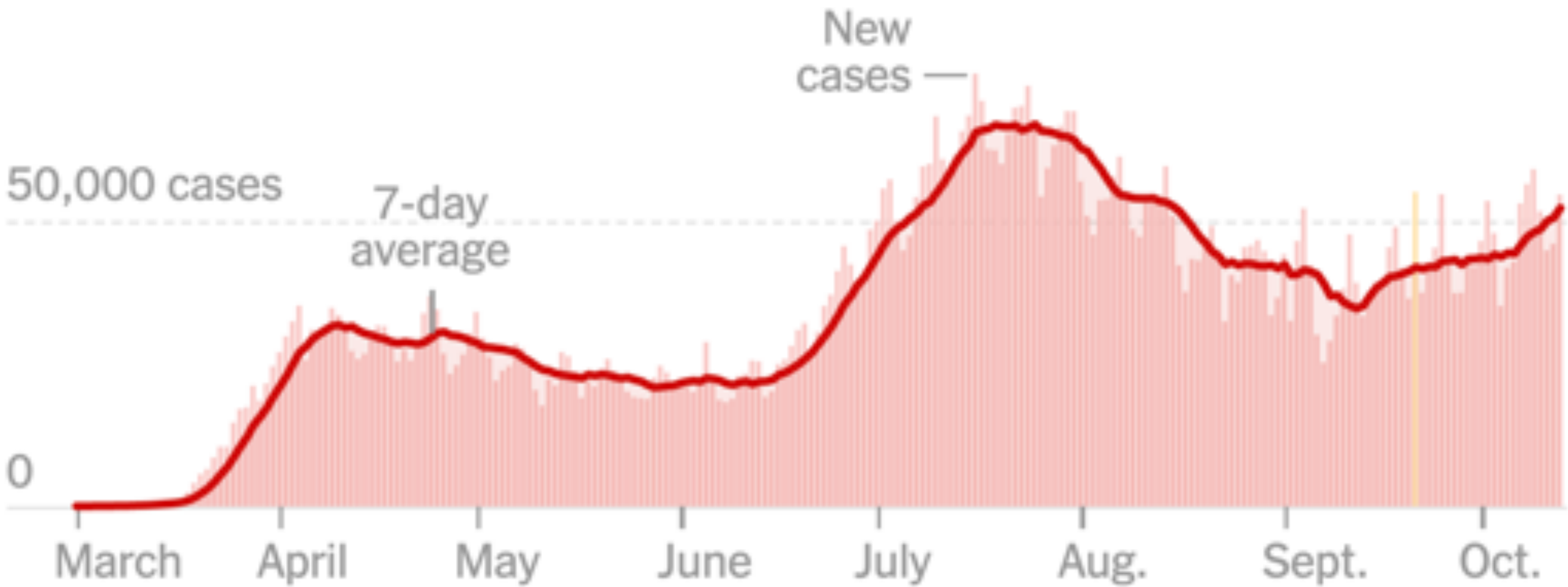


image credit: NY Times

COVID-19 Forecast Hub Timeline

Early 2020: Nick enjoying sabbatical in Munich

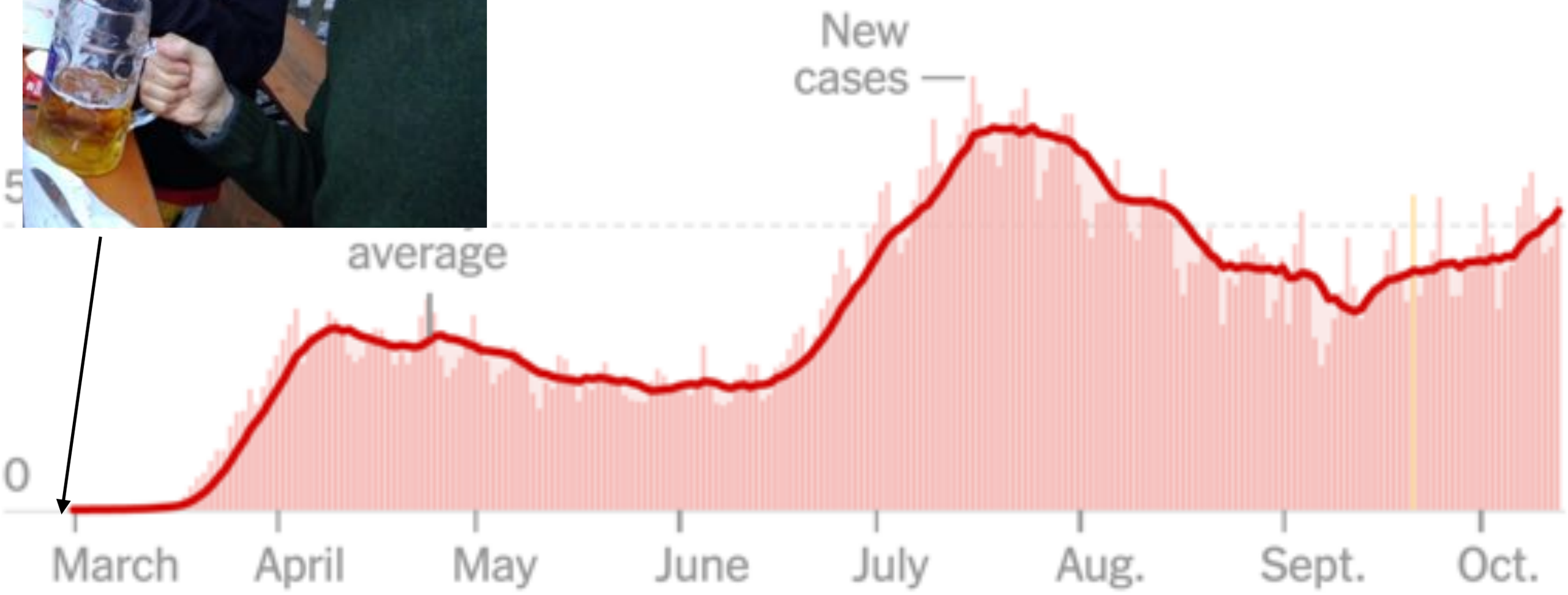


image credit: NY Times

COVID-19 Forecast Hub Timeline

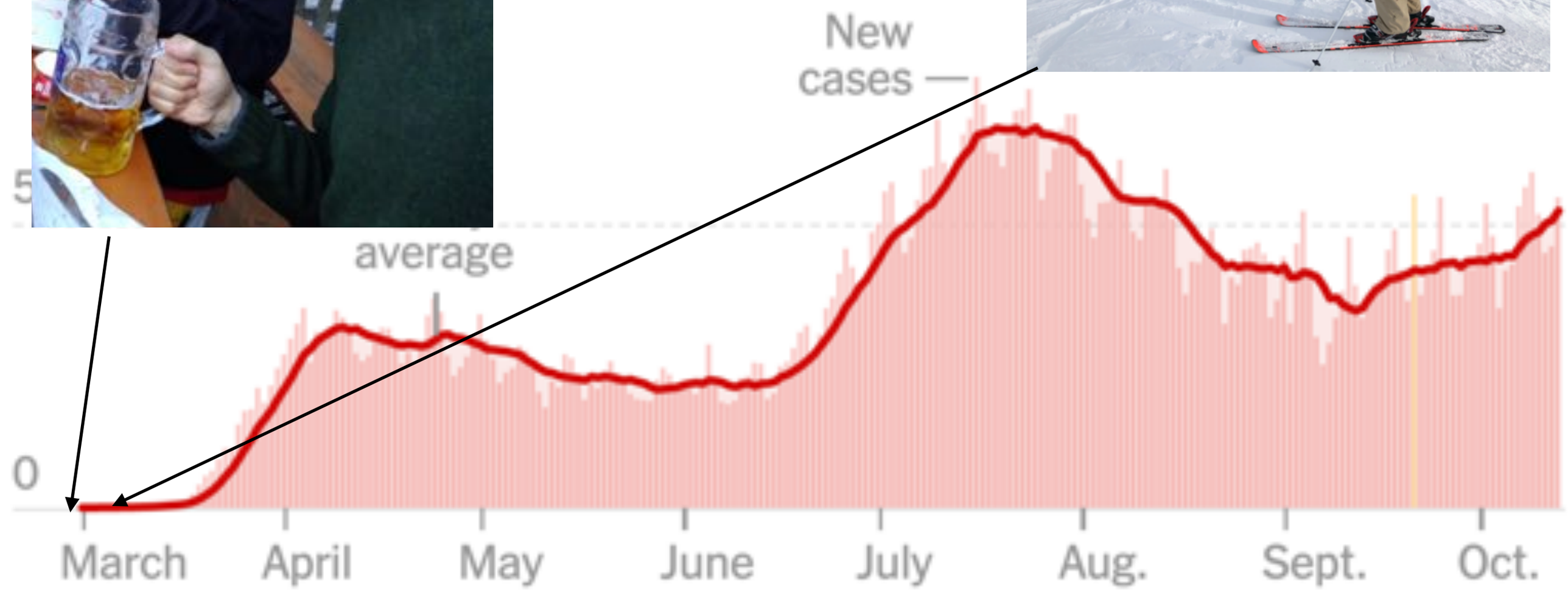


image credit: NY Times

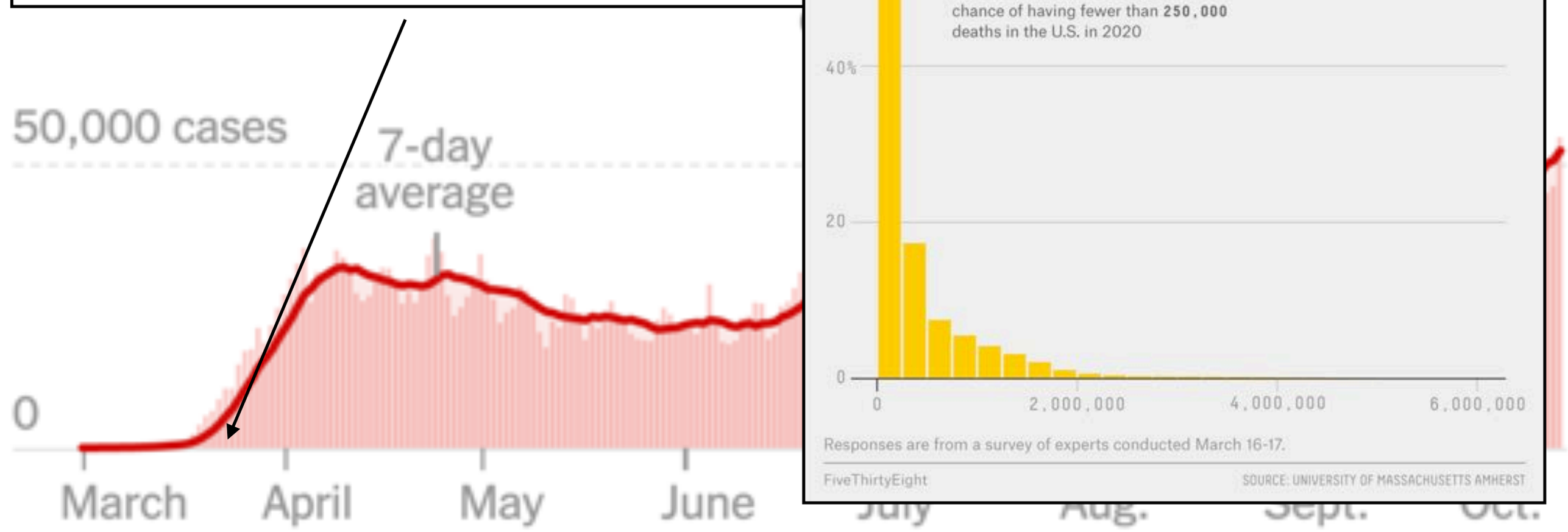
COVID-19 Forecast Hub Timeline


FiveThirtyEight

Politics Sports **Science** Podcasts Video

MAR. 20, 2020, AT 5:01 PM

Infectious Disease Experts Don't Know How Bad The Coronavirus Is Going To Get, Either



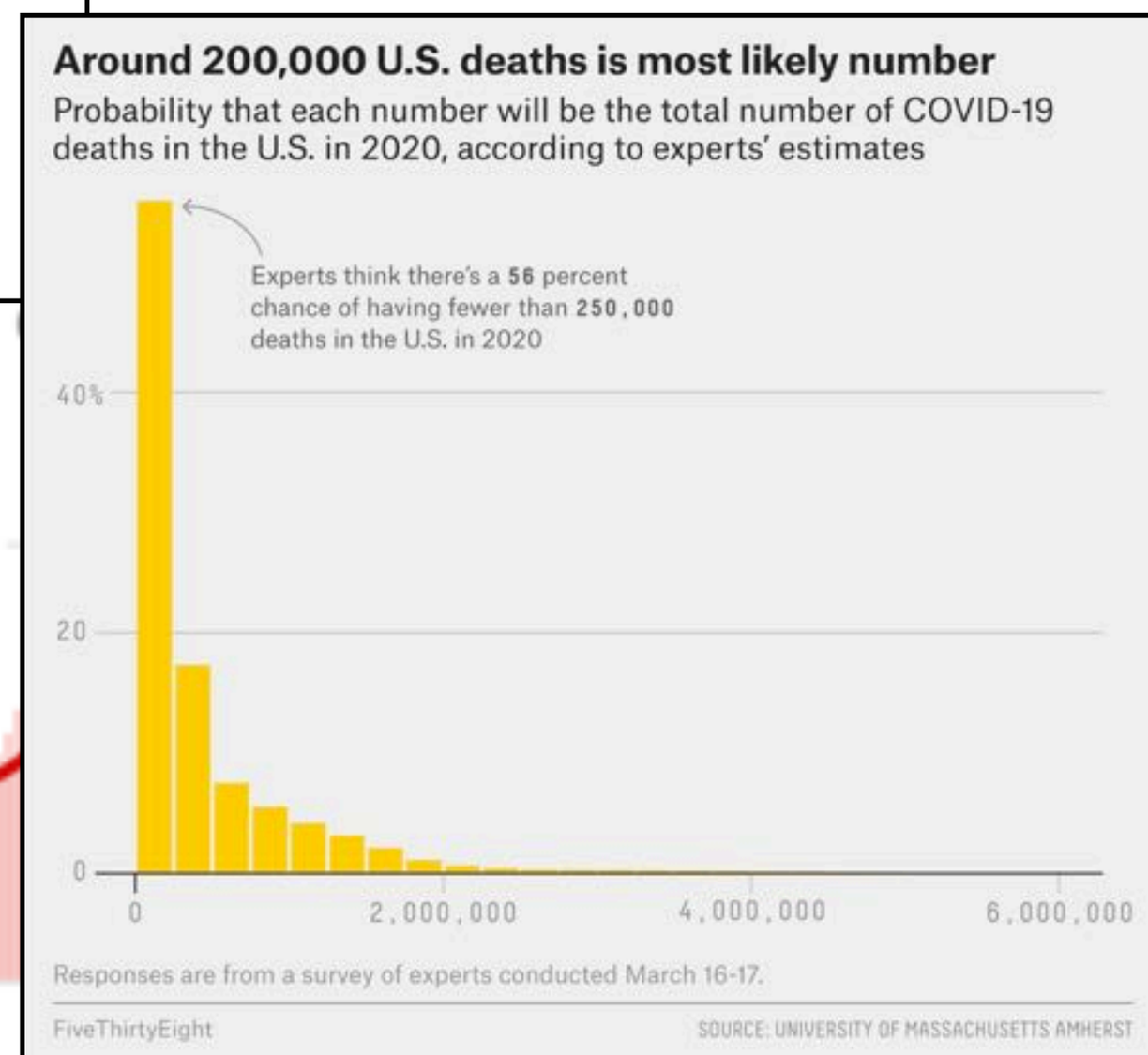


image credit: NY Times

COVID-19 Forecast Hub Timeline

Late March: First projections from Columbia University and IHME
Early April: First projections from Los Alamos Nat'l Labs

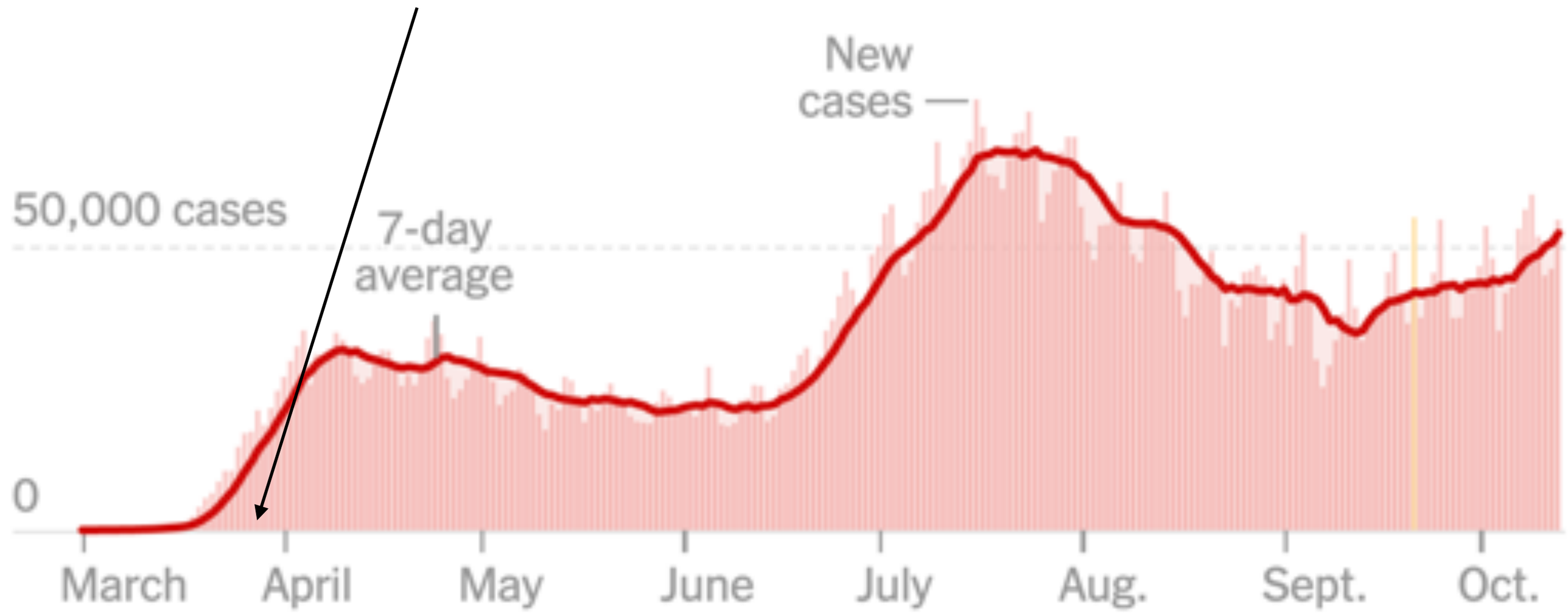


image credit: NY Times

COVID-19 Forecast Hub Timeline

April 5, 2020: COVID-19 Forecast Hub GitHub repository created

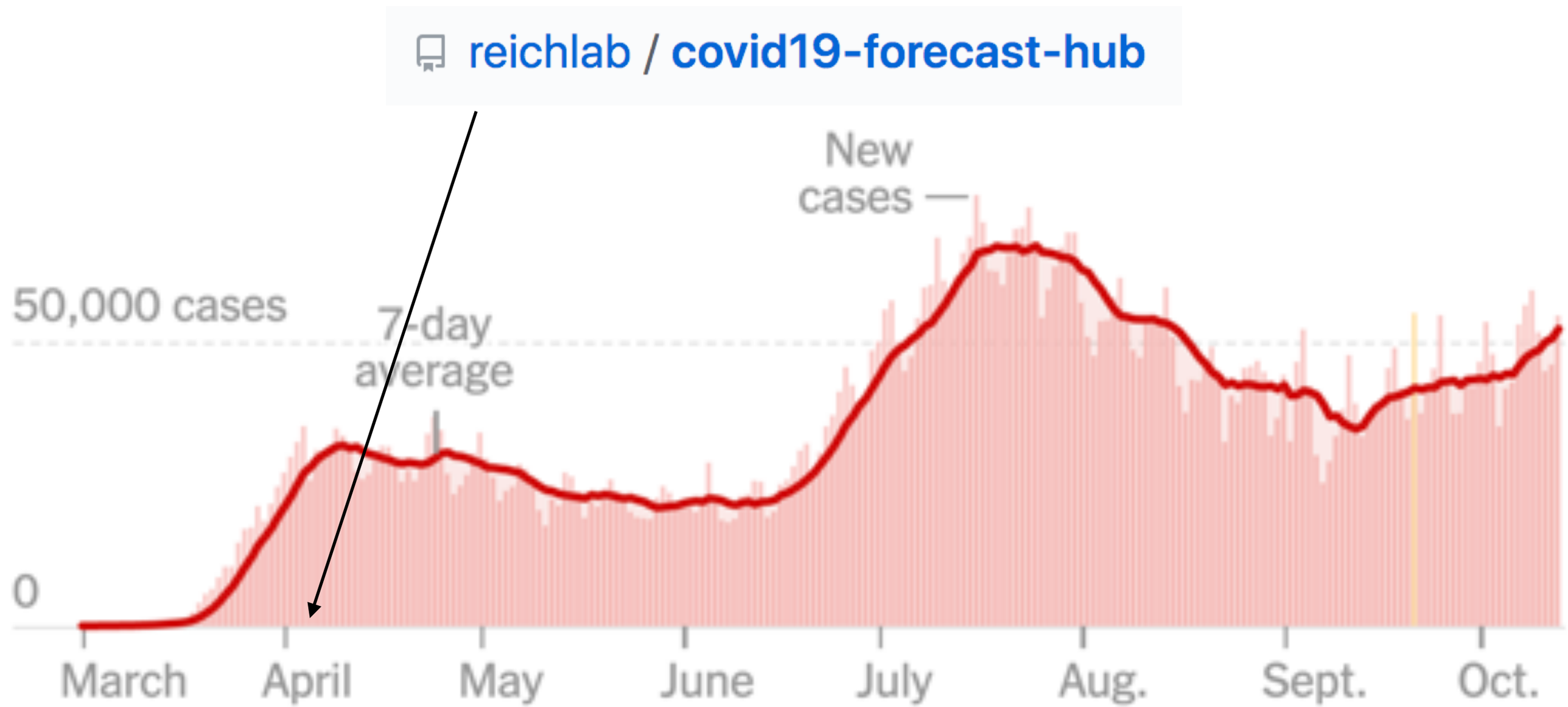
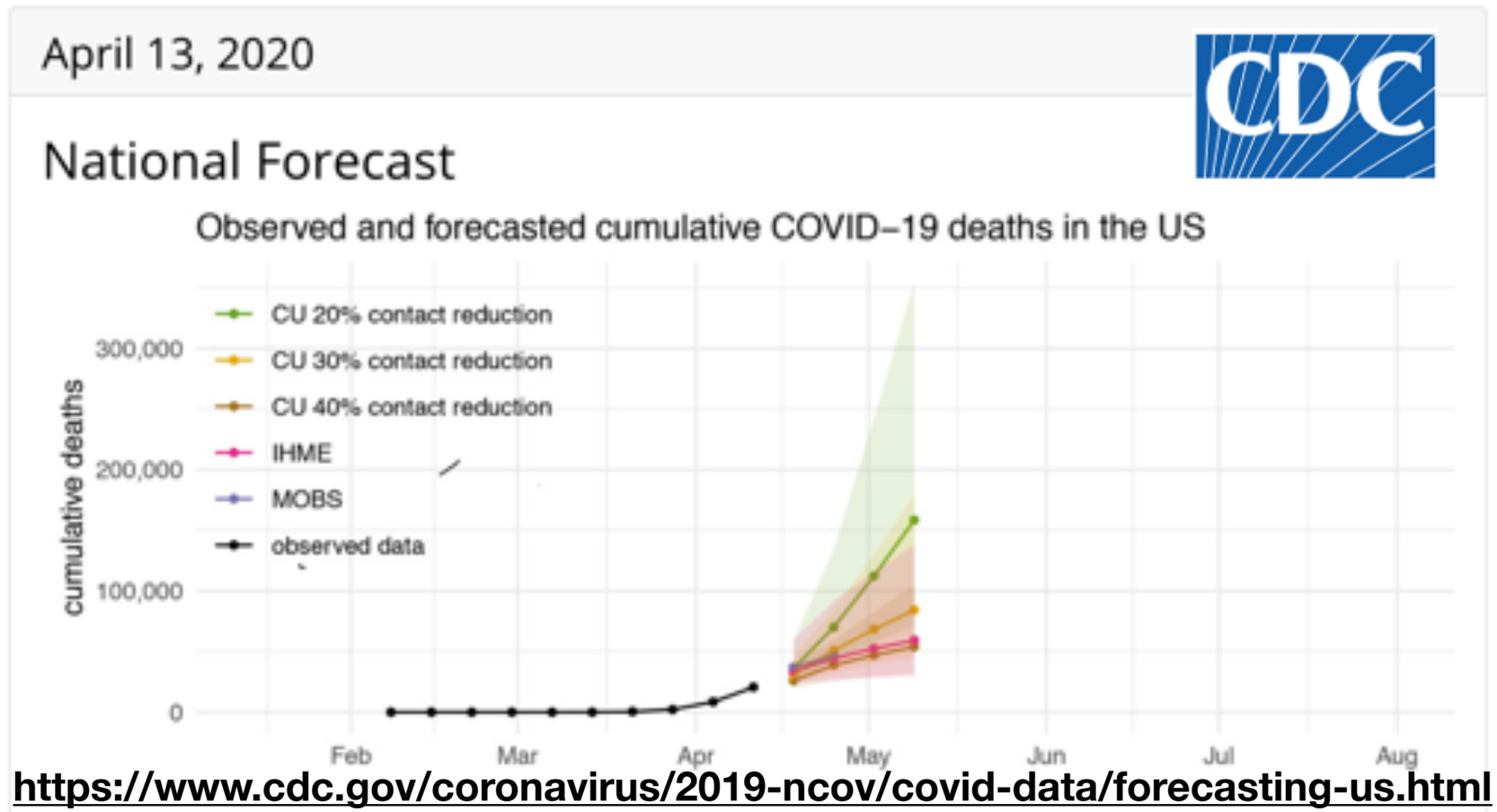


image credit: NY Times

COVID-19 Forecast Hub Timeline

April 13, 2020:
first Hub forecasts displayed on CDC website.
3 teams.



https://www.cdc.gov/coronavirus/2019-ncov/covid-data/forecasting-us.html

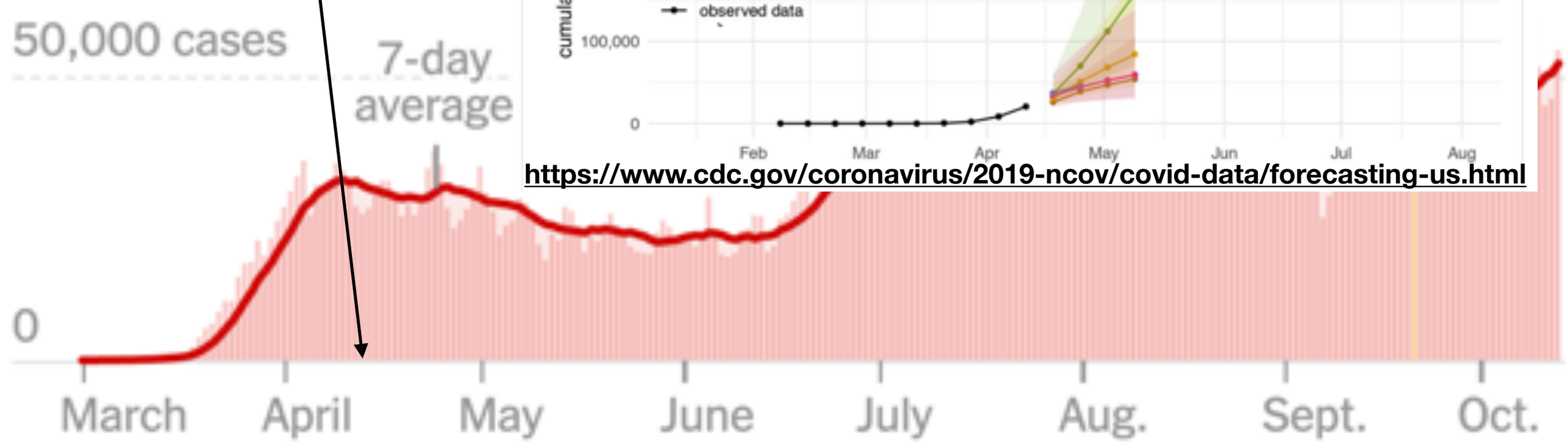


image credit: NY Times

COVID-19 Forecast Hub Timeline

April 22, 2020:
Jarad Niemi joins
COVID-19
Forecast Hub

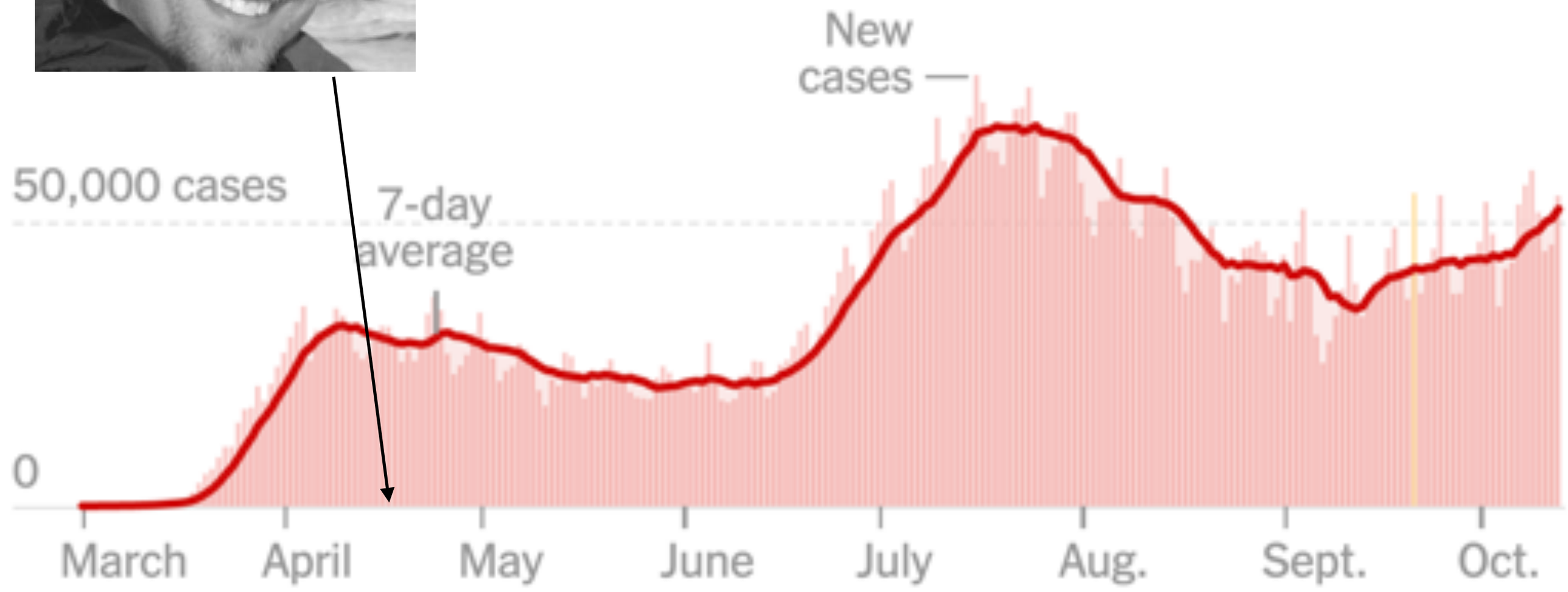
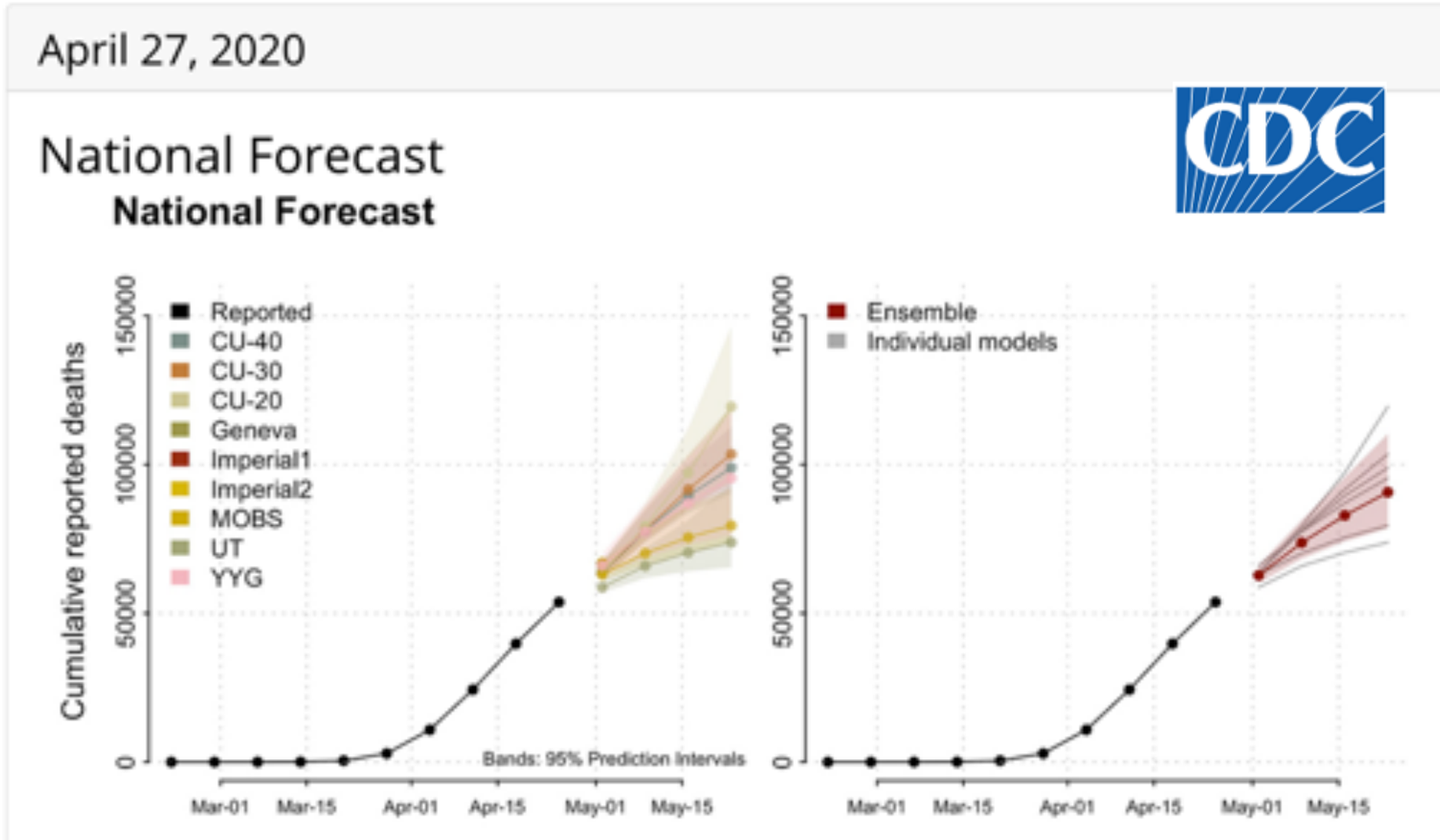


image credit: NY Times

COVID-19 Forecast Hub Timeline

April 27, 2020: first Hub ensemble forecast on CDC website. 6 teams.



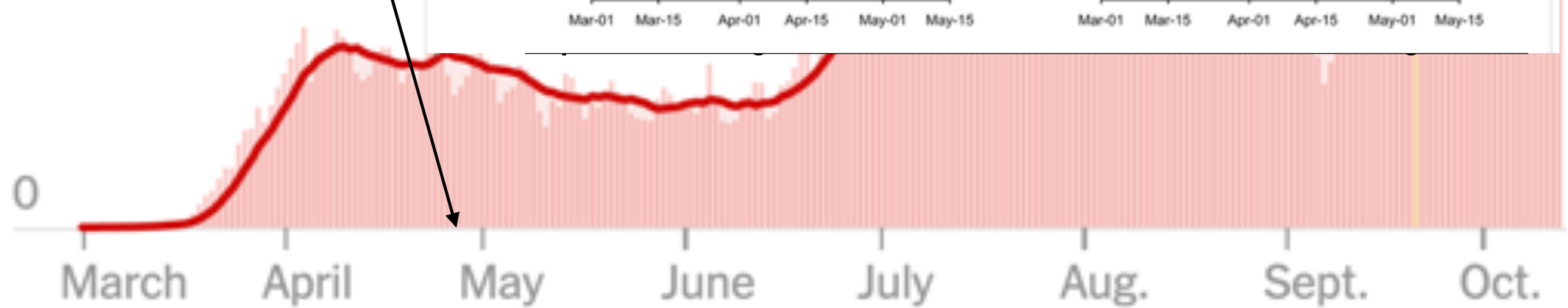
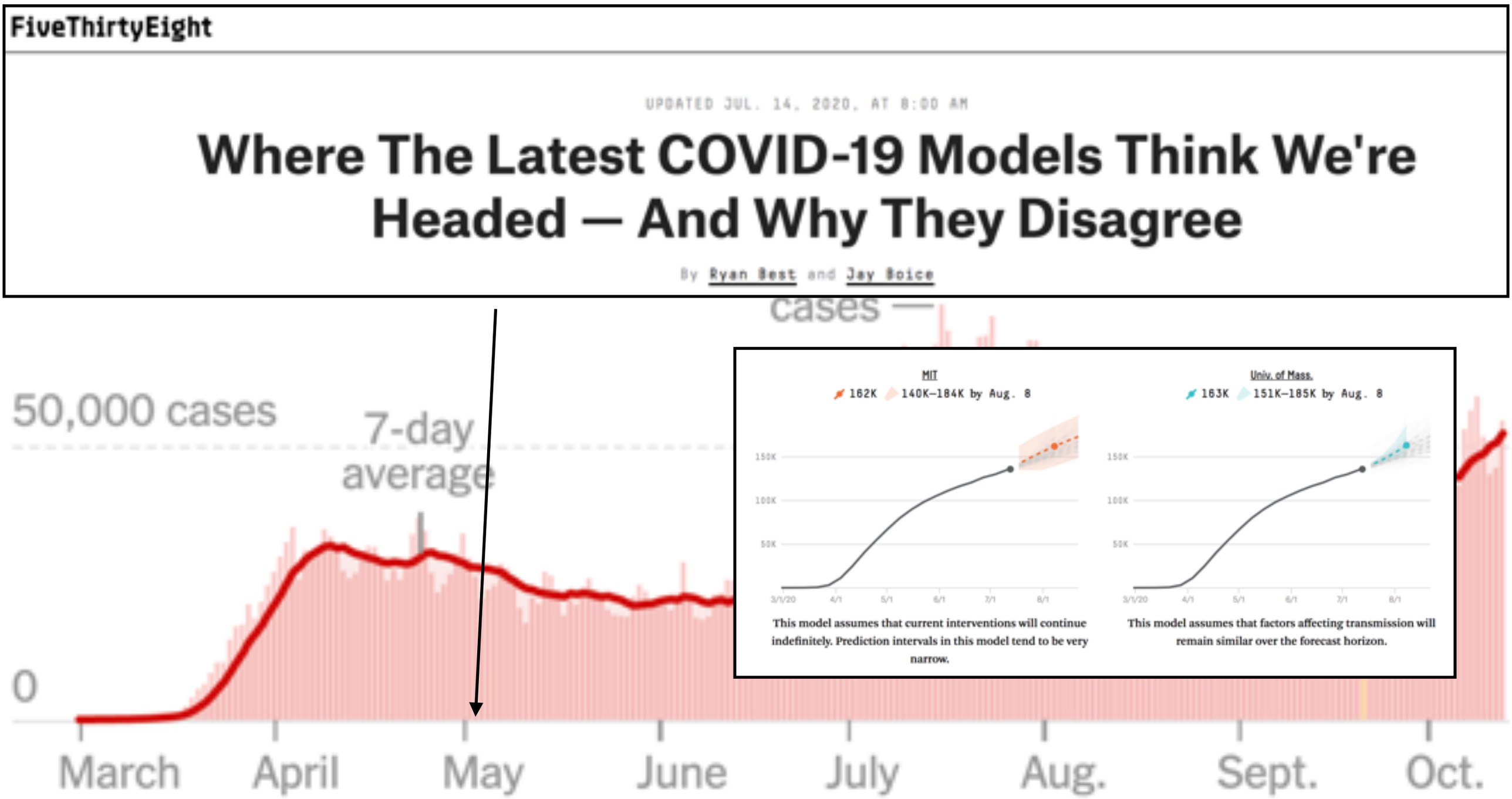


image credit: NY Times

COVID-19 Forecast Hub Timeline

May 1, 2020

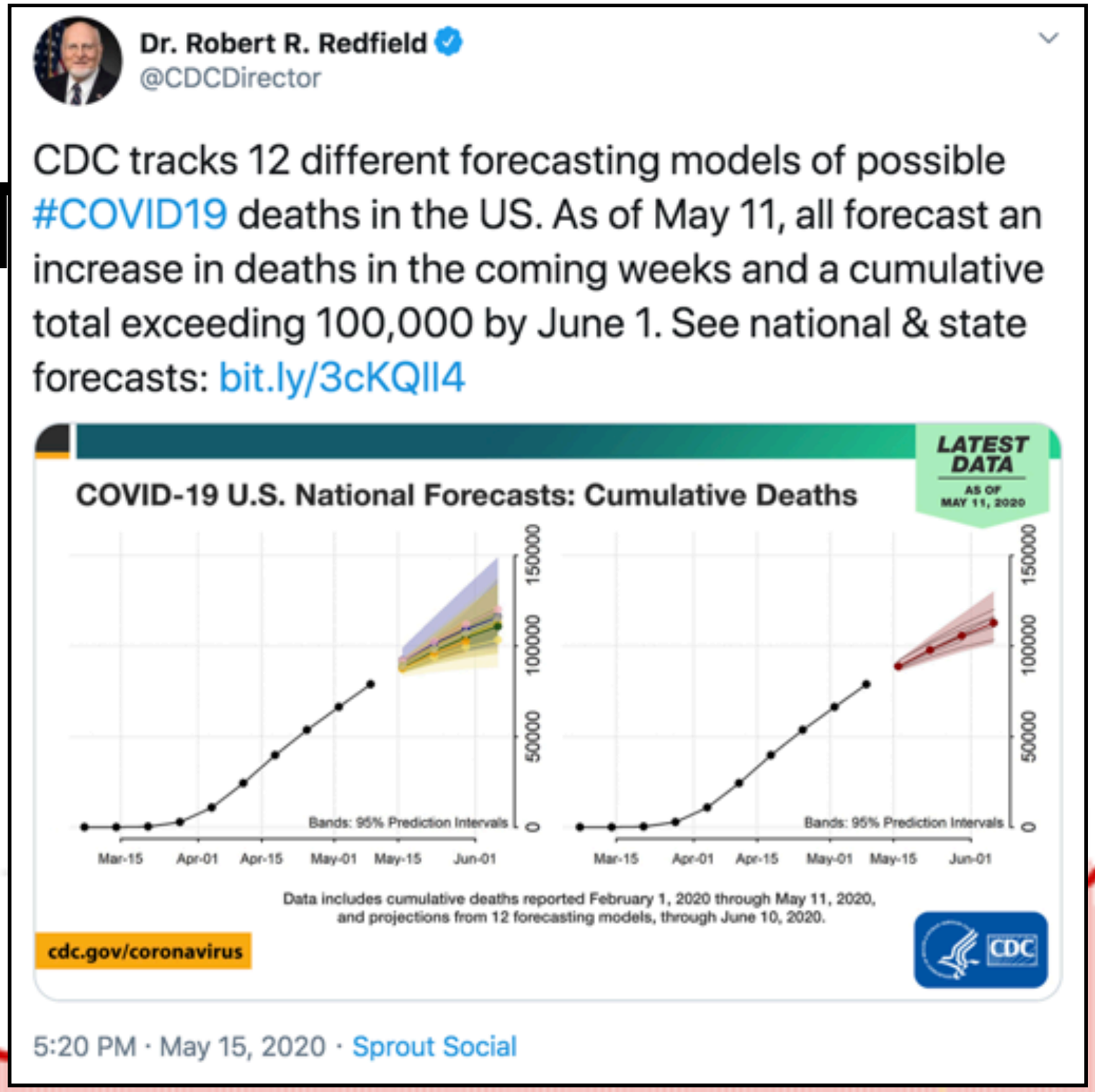


https://projects.fivethirtyeight.com/covid-forecasts/

image credit: NY Times

COVID-1
T

May 15, 2020:
Director Redfield tweets out results. CDC forecasting website viewed by >1m visitors.
11 teams.



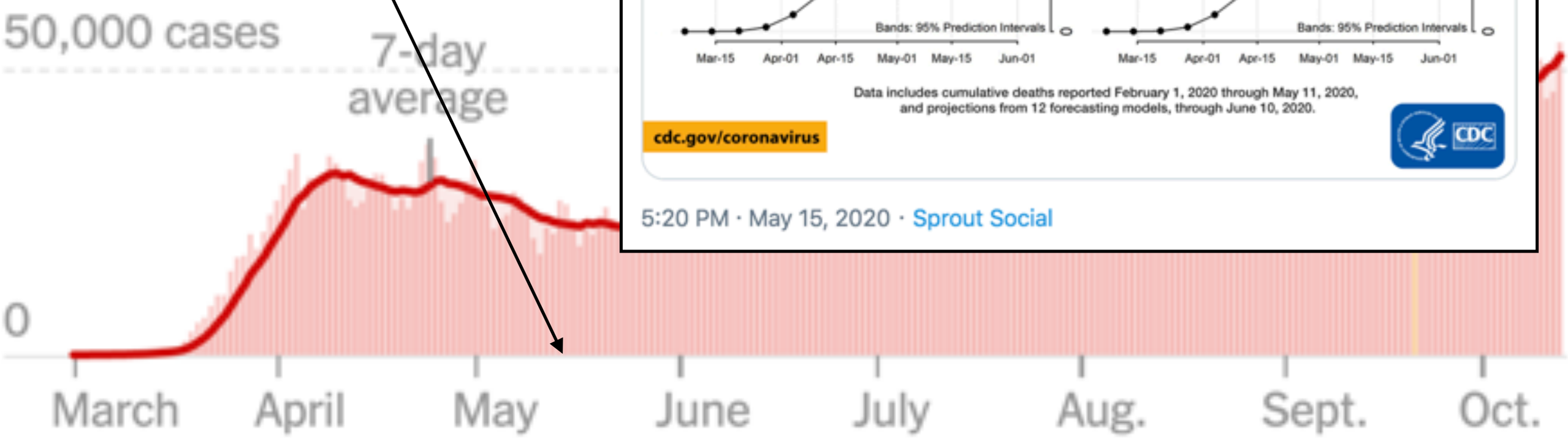


image credit: NY Times

COVID-19 Forecast Hub

June 4, 2020:
20 teams

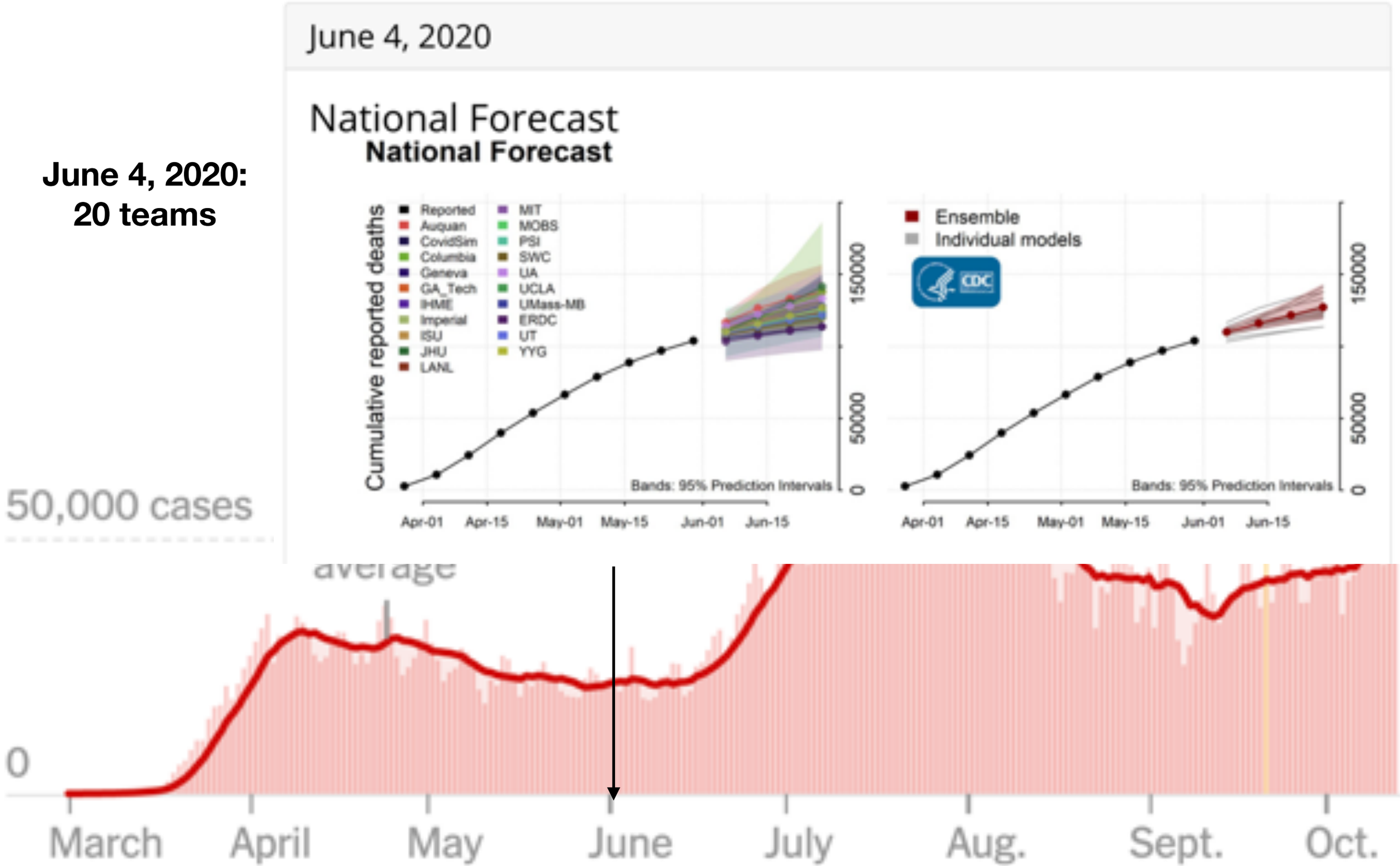
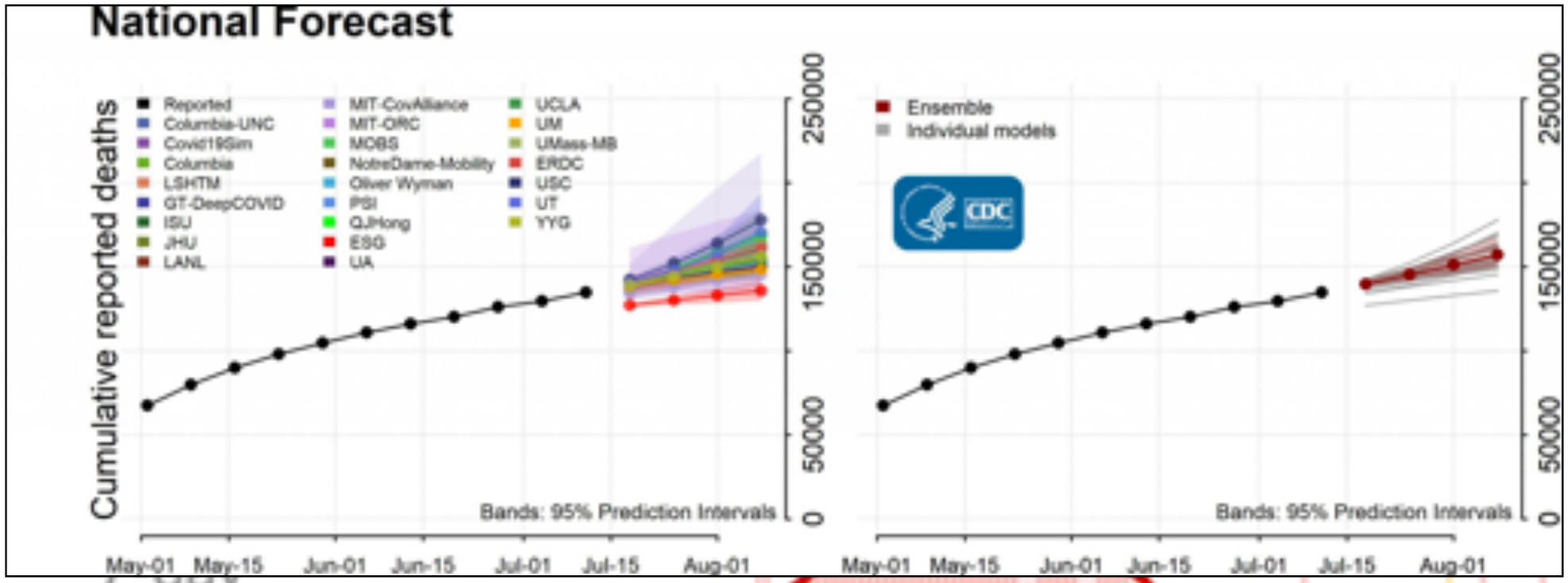


image credit: NY Times

COVID-19 Forecast Hub Timeline

July 15, 2020:
24 teams



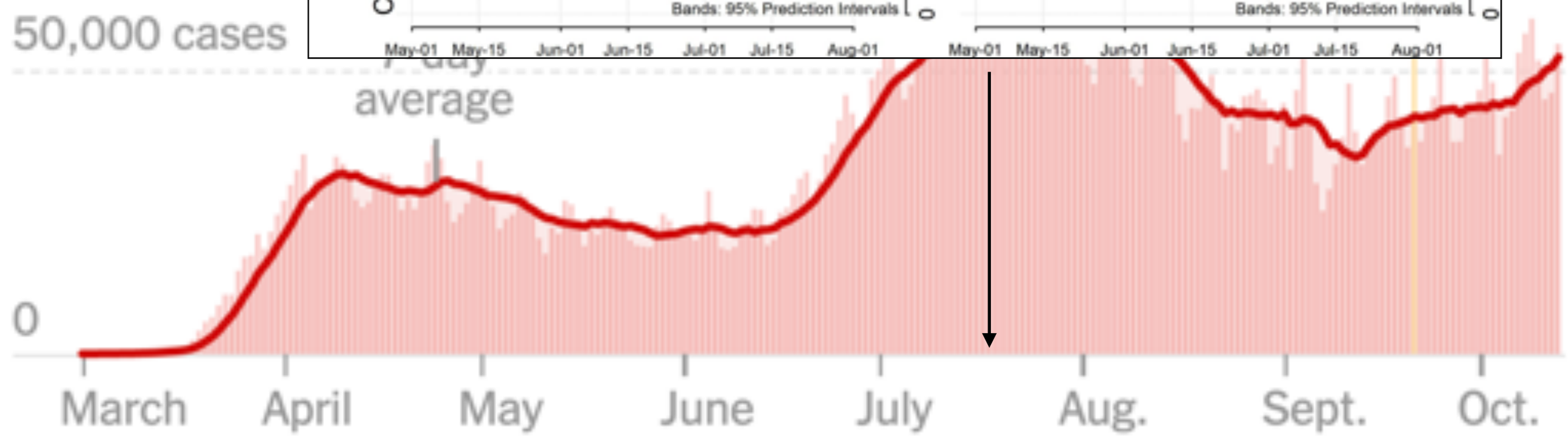


image credit: NY Times

COVID-19 Forecast Hub Timeline

Oct 15, 2020:
36 teams

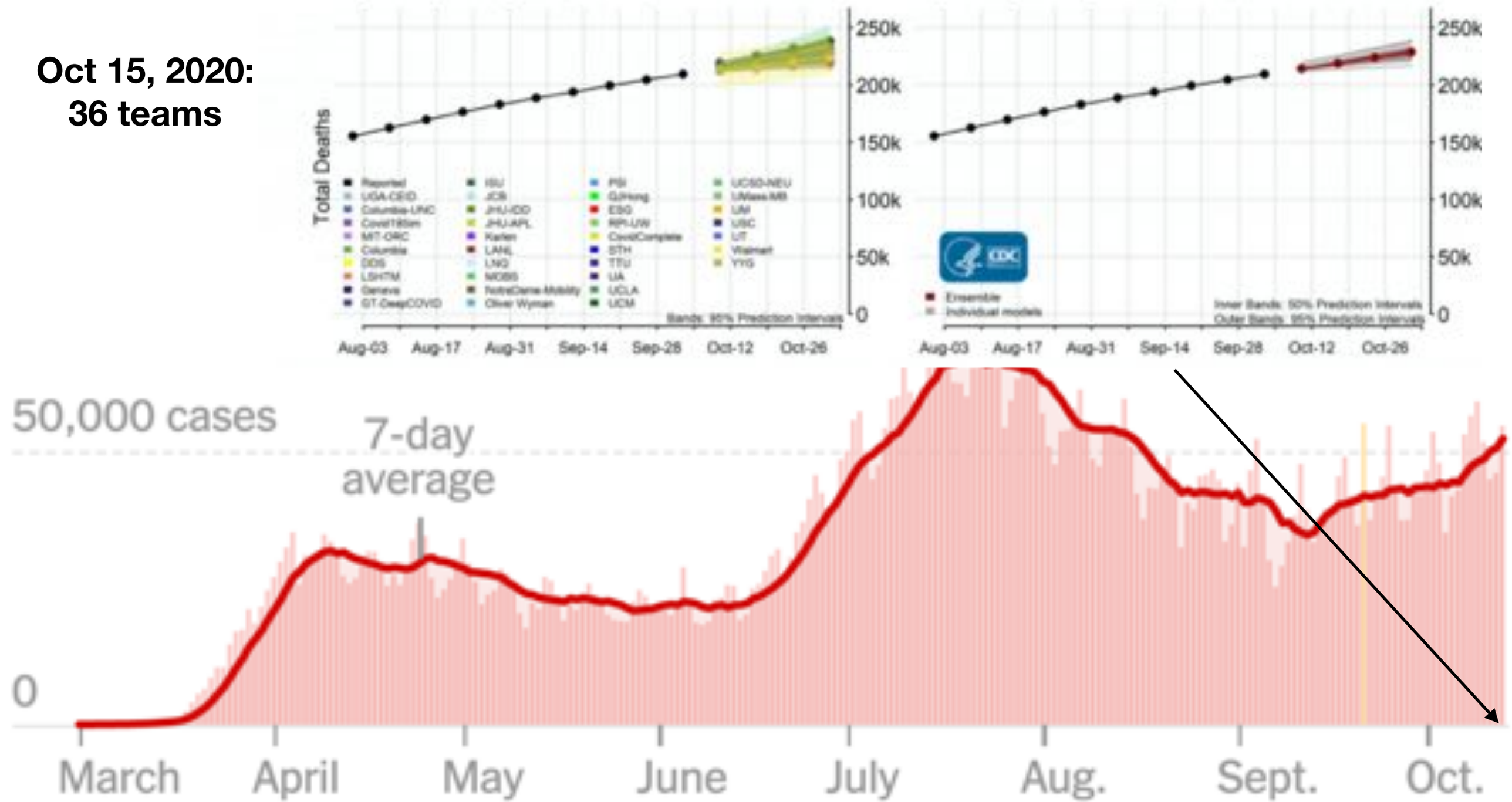


image credit: NY Times

How did we get here?

What are we doing?

How accurate are these models?

COVID-19
ForecastHub

How did we get here?

From a long-standing forecasting collaboration with CDC.

What are we doing?

We are building some simple ensemble models.

How accurate are these models?

A little bit more accurate than a naive baseline model, but not much.

COVID-19 ForecastHub

Forecasting Seasonal Flu

CDC FluSight challenges: U.S. national, regional, state forecasts

Target variable "weighted ILI":
The % of all outpatient visits with primary complaint of influenza-like illness (ILI), weighted by state population.

https://www.cdc.gov/flu/weekly/flusight

CDC Centers for Disease Control and Prevention
CDC 24/7: Saving Lives, Protecting People™

SEARCH

CDC A-Z INDEX

Influenza (Flu)

- Seasonal Influenza (Flu)
- About Flu +
- Flu Season +
- Prevent Flu +
- Symptoms & Diagnosis +
- Treatment +
- Schools, Businesses & Travelers +
- Flu Activity & Surveillance −
  - CDC's WHO Collaborating Center
  - Situation Update: Summary of Weekly

Seasonal Influenza (Flu) › Flu Activity & Surveillance

FluSight: Flu Forecasting

Language: English (US)

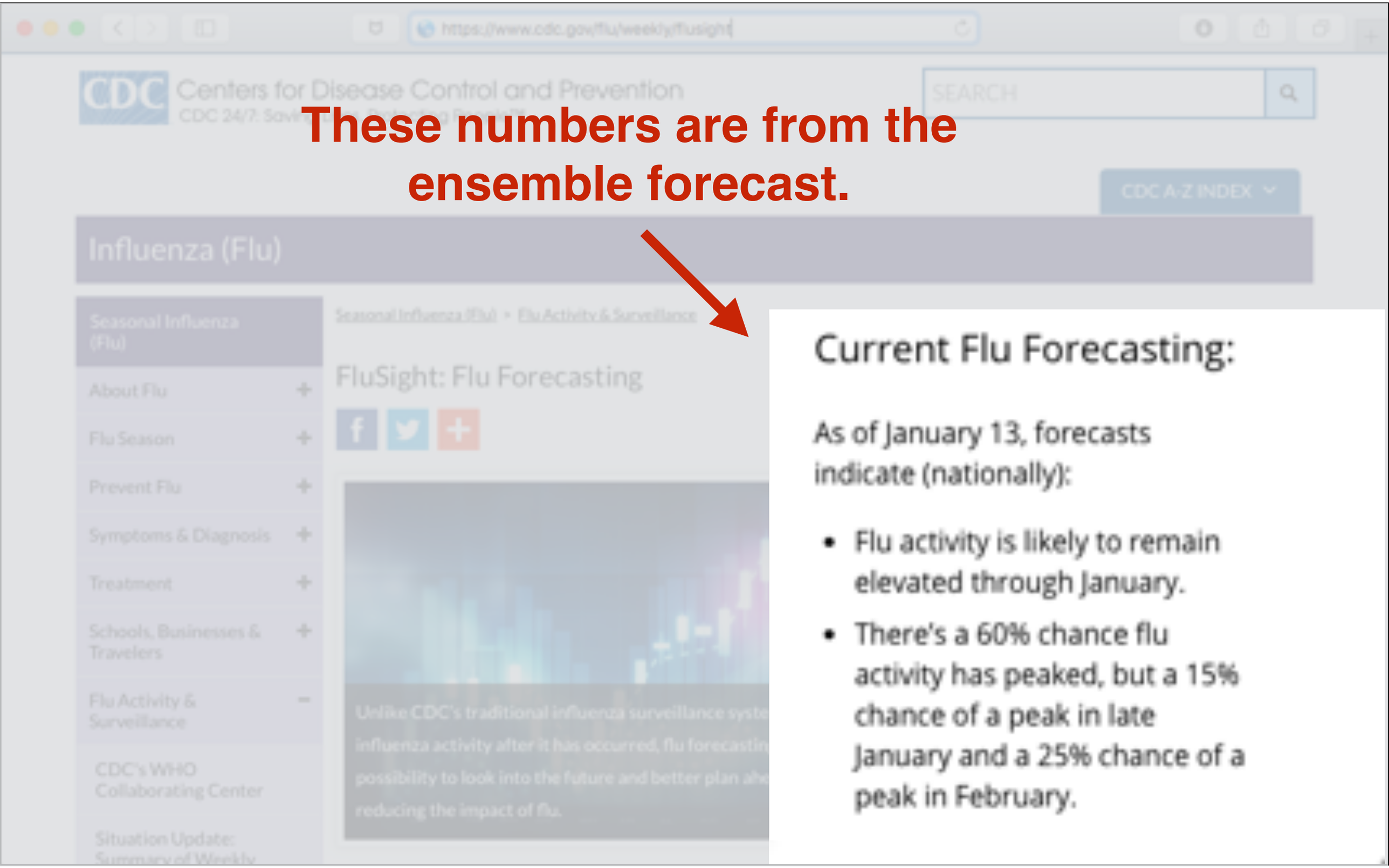
Current Flu Forecasting:

As of January 13, forecasts indicate (nationally):

- Flu activity is likely to remain elevated through January.
- There's a 60% chance flu activity has peaked, but a 15% chance of a peak in late January and a 25% chance of a peak in February.

CDC website launched Jan 4, 2019

These numbers are from the ensemble forecast.



CDC website launched Jan 4, 2019

scientific reports

Explore our content Journal information

nature > scientific reports > articles > article

Article | Open Access | Published: 24 January 2019

Collaborative efforts to forecast seasonal influenza in the United States, 2015–2016

Craig J. McGowan, Matthew Biggerstaff, Michael Johansson, Karyn M. Apfeldorf, Michal Ben-Nun, Logan Brooks, Matteo Convertino, Madhav Erraguntla, David C. Farrow, John Freeze, Saurav Ghosh, Sangwon Hyun, Sasikiran Kandula, Joceline Lega, Yang Liu, Nicholas Michaud, Haruka Morita, Jarad Niemi, Naren Ramakrishnan, Evan L. Ray, Nicholas G. Reich, Pete Riley, Jeffrey Shaman, Ryan Tibshirani, Alessandro Vespignani, Qian Zhang, Carrie Reed & The Influenza Forecasting Working Group -Show fewer authors

From the abstract:

“Higher forecast skill was associated with team participation in previous influenza forecasting challenges and utilization of ensemble forecasting techniques. The mean ensemble consistently performed well and outperformed historical trend predictions.”

PLOS | COMPUTATIONAL BIOLOGY

RESEARCH ARTICLE

Accuracy of real-time multi-model ensemble forecasts for seasonal influenza in the U.S.

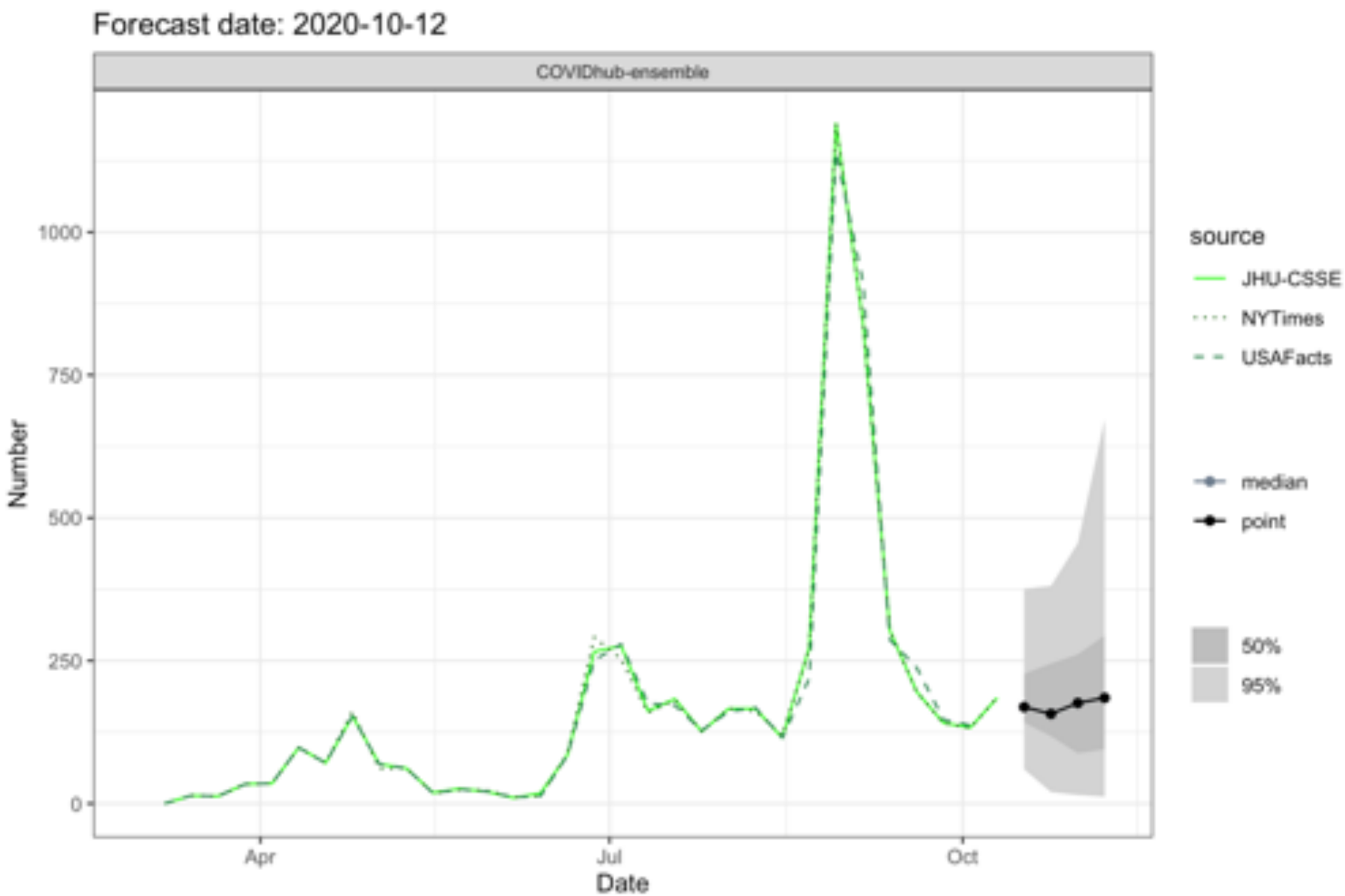
Nicholas G. Reich[1*], Craig J. McGowan[2], Teresa K. Yamana[3], Abhinav Tushar[4], Evan L. Ray[5], Dave Osthus[6], Sasikiran Kandula[3], Logan C. Brooks[7], Willow Crawford-Crudell[8], Graham Casey Gibson[1], Evan Moore[1], Rebecca Silva[9], Matthew Biggerstaff[2], Michael A. Johansson[10], Roni Rosenfeld[11], Jeffrey Shaman[3]

"This approach creates a weighted average of predictive densities where the weight for each component is determined by maximizing overall ensemble accuracy over past seasons. In the 2017/2018 influenza season, one of the largest seasonal outbreaks in the last 15 years, this multi-model ensemble performed better on average than all individual component models and placed second overall in the CDC challenge. ... **This project shows that collaborative efforts between research teams to develop ensemble forecasting approaches can bring measurable improvements in forecast accuracy and important reductions in the variability of performance from year to year**."

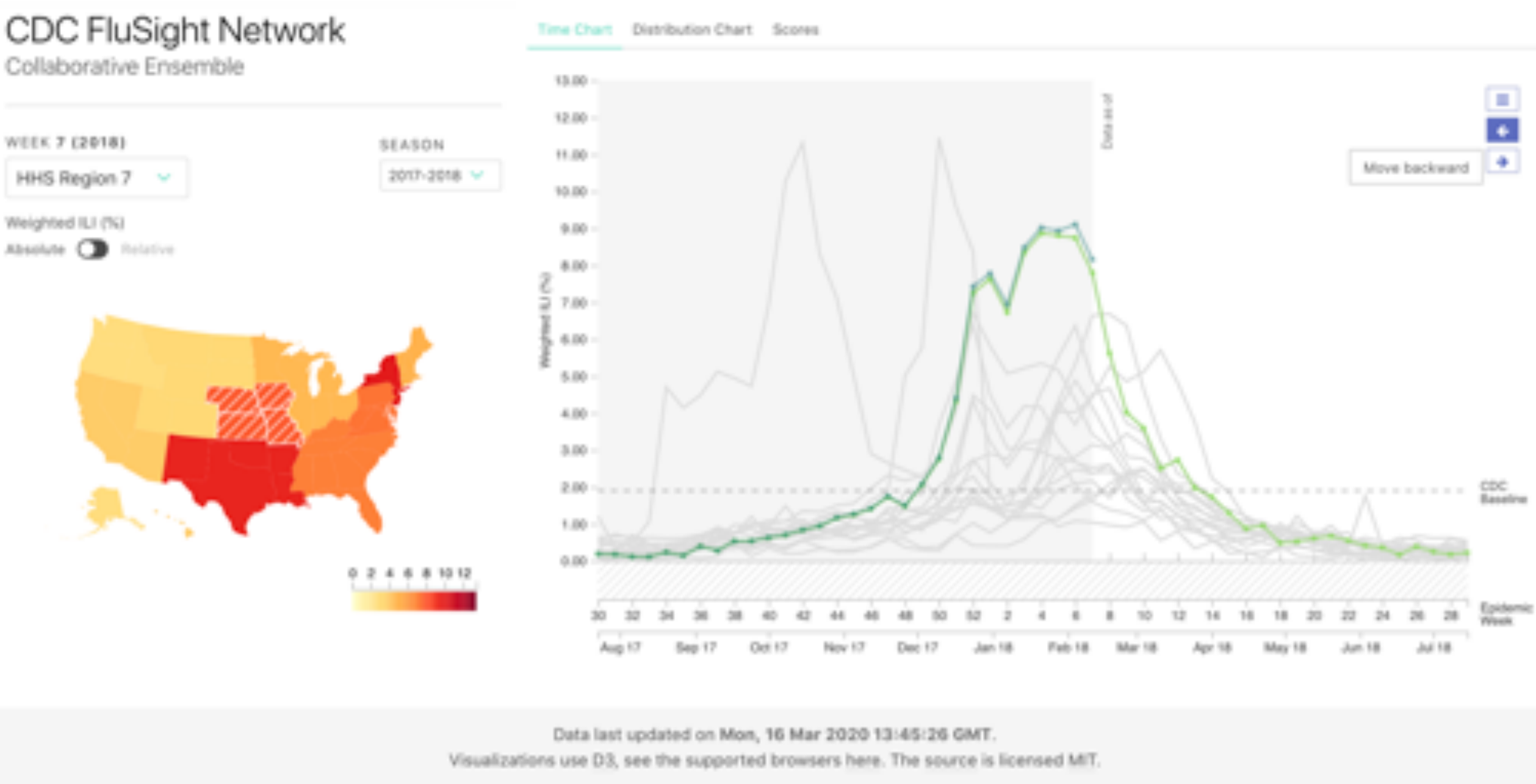
Truth Data

COVID-19
ForecastHub

Johnson County, Iowa
Truth discrepancy



ILI Backfill

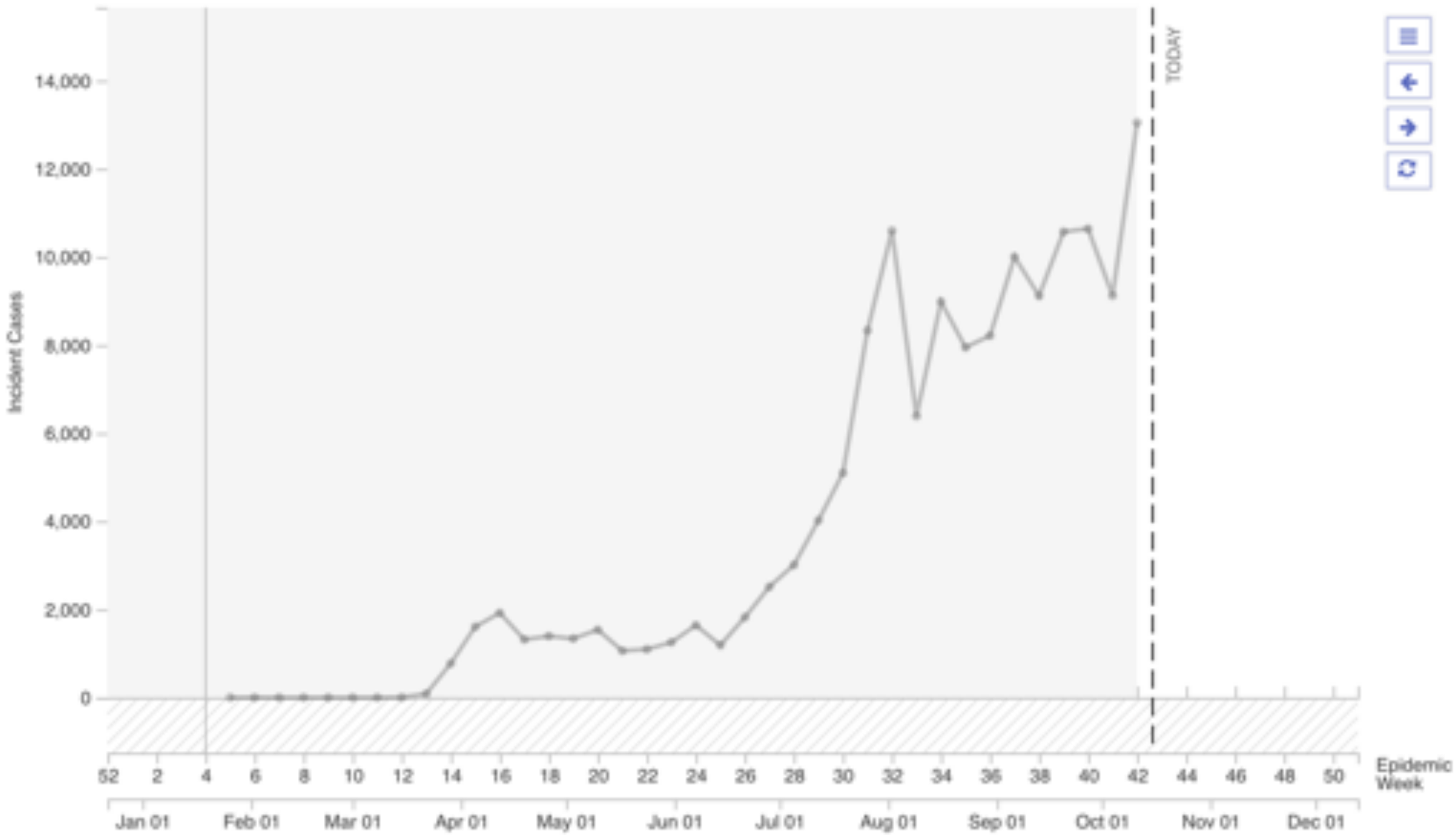


flusightnetwork.io

Missouri COVID-19 Backfill

github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data

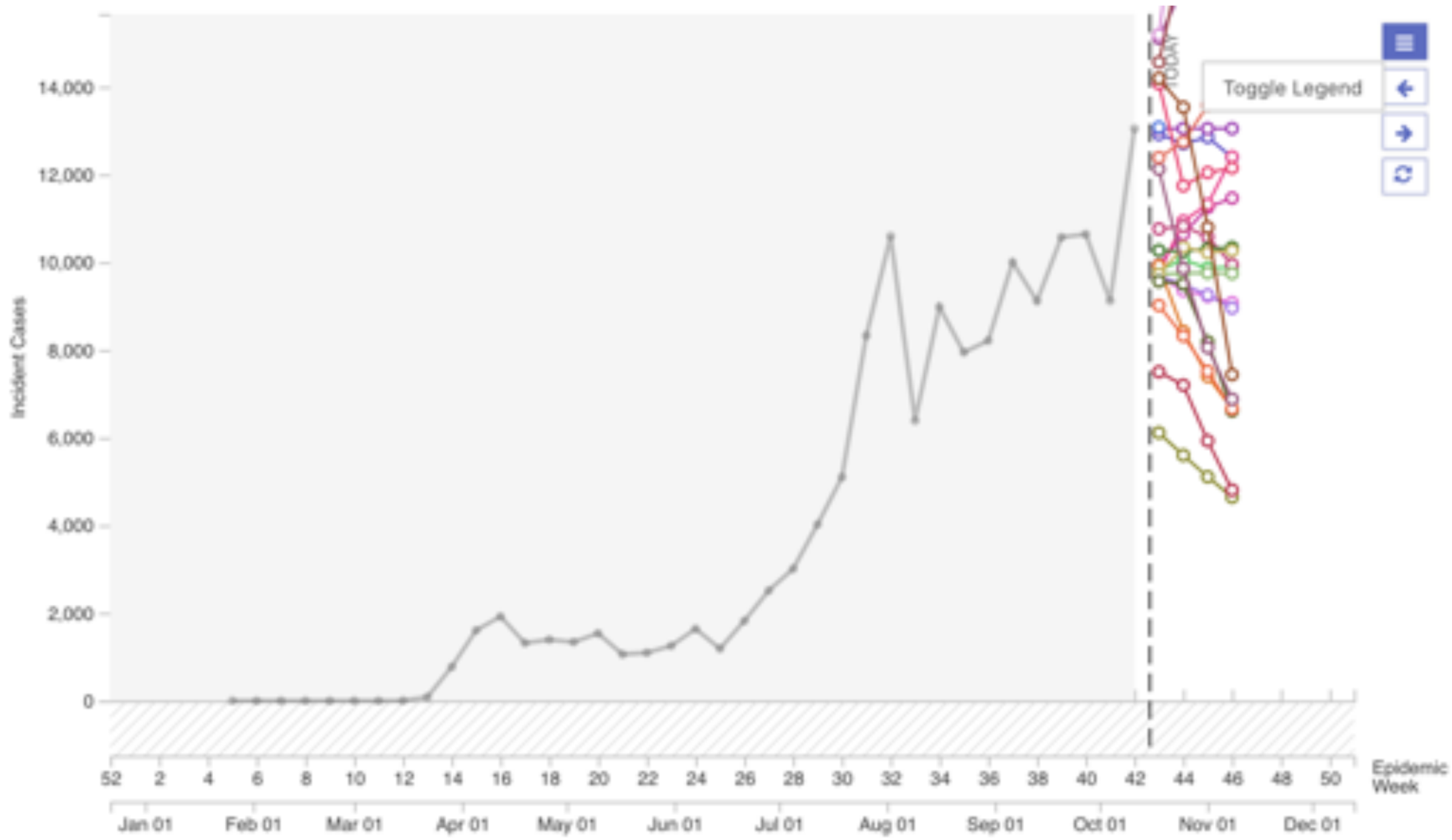
October 12, spike in cases in the State of Missouri is due to a database error. We are monitoring the dashboard and will redistribute if the error is fixed. News report



Missouri COVID-19 Forecasts

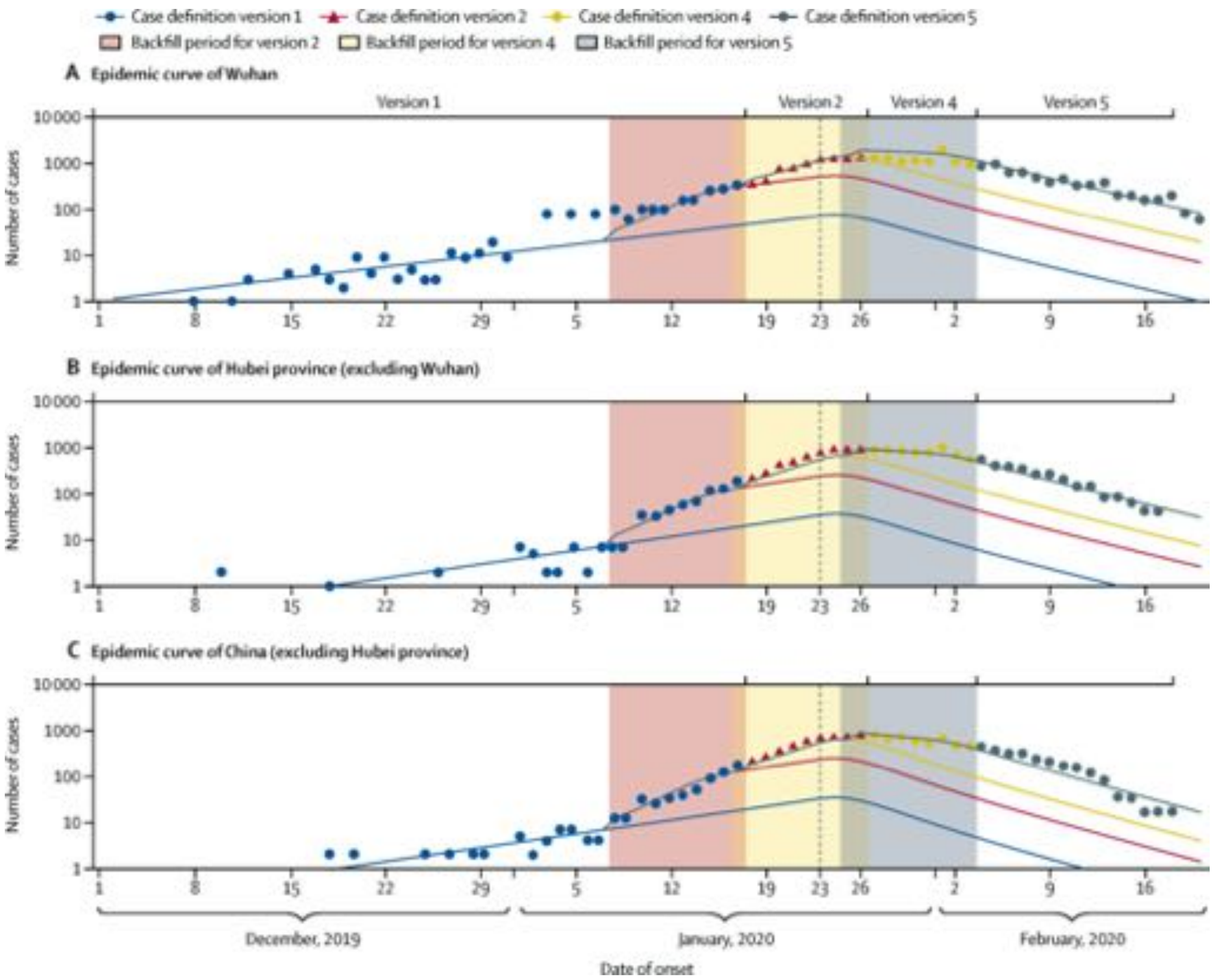
github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data

October 12, spike in cases in the State of Missouri is due to a database error. We are monitoring the dashboard and will redistribute if the error is fixed. News report



China COVID-19 Backfill

www.thelancet.com/journals/lanpub/article/PIIS2468-2667(20)30089-X/fulltext



COVID-19 Backfill

COVID-19 backfill questions:

- **Should models be required to model backfill?**
  - **No:**
    - **Just a data artifact, not interesting**
  - **Yes:**
    - **Check for non-negative incident, but backfill causes negative values**
    - **Evaluate models based on observed data**

- **Should models be required to target JHU CSSE data?**
  - **No:**
    - **JHU CSSE data choice was arbitrary**
    - **The Hub can model an “offset”**
  - **Yes:**
    - **If you want your model to be evaluated fairly, yes.**

Forecast collection

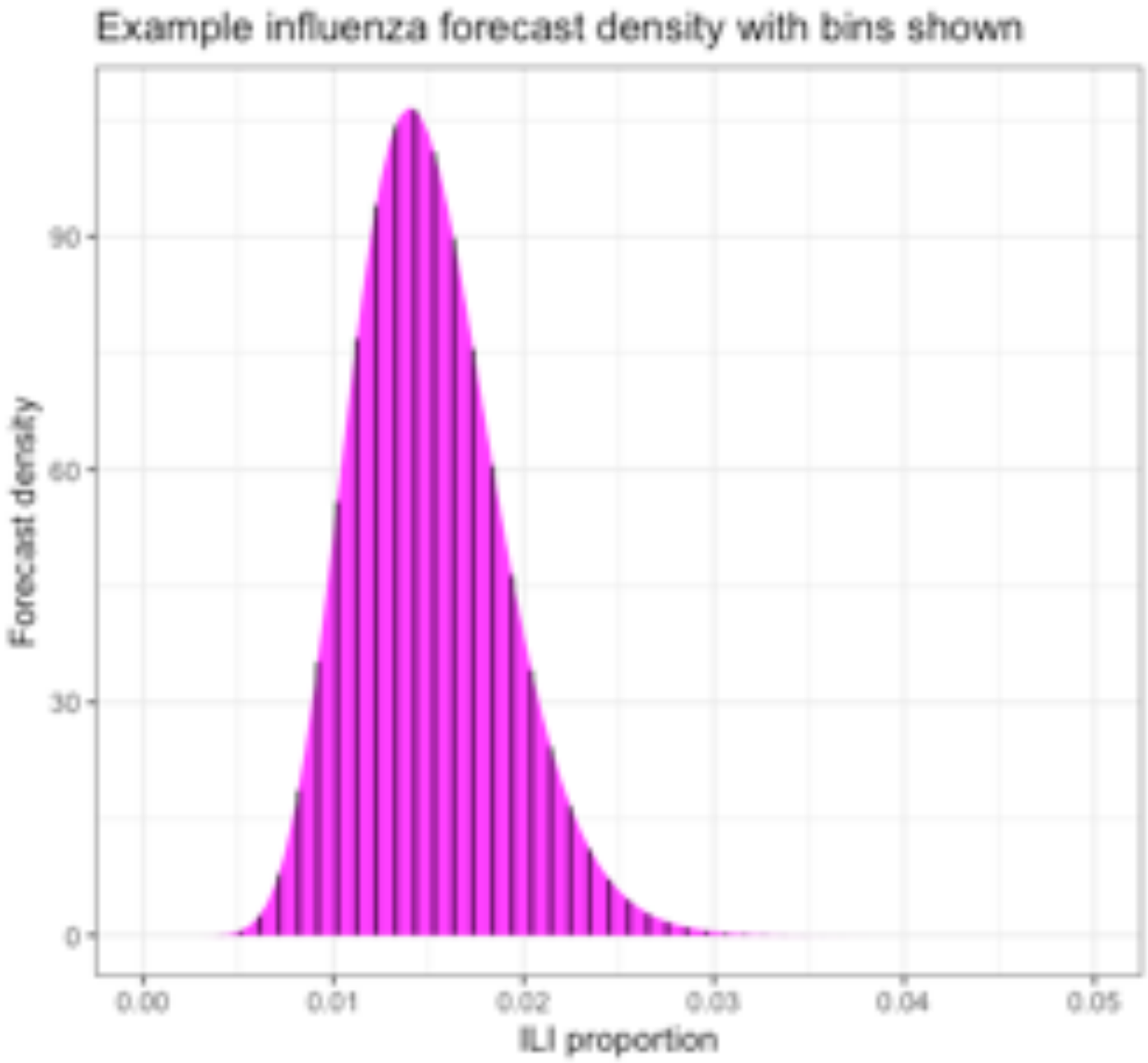
COVID-19
ForecastHub

Standardization

github.com/reichlab/covid19-forecast-hub/wiki/Forecast-Checks

- checks `value` must be an int or float and non-negative
- validates date alignment as documented in the issue add additional validations
- validates quantiles and values (i.e,. at the prediction level):
  - checks that entries in `value` must be non-decreasing as quantiles increase
  - checks that elements in the `quantile` are unique
- validates quantiles as a group:
  - there must be exactly one point prediction for each `location/target` pair
- validates if the prediction `value` for a location is at least less than the population of that location.
  - this check is run for all forecast submissions for all targets (in/cum deaths/cases).
  - the population truth data is present in the locations.csv file.
  - To check which predictions are violating, check the logs in the Github Actions build do your PR and it should be printed.

Probabilistic ILI Forecasts



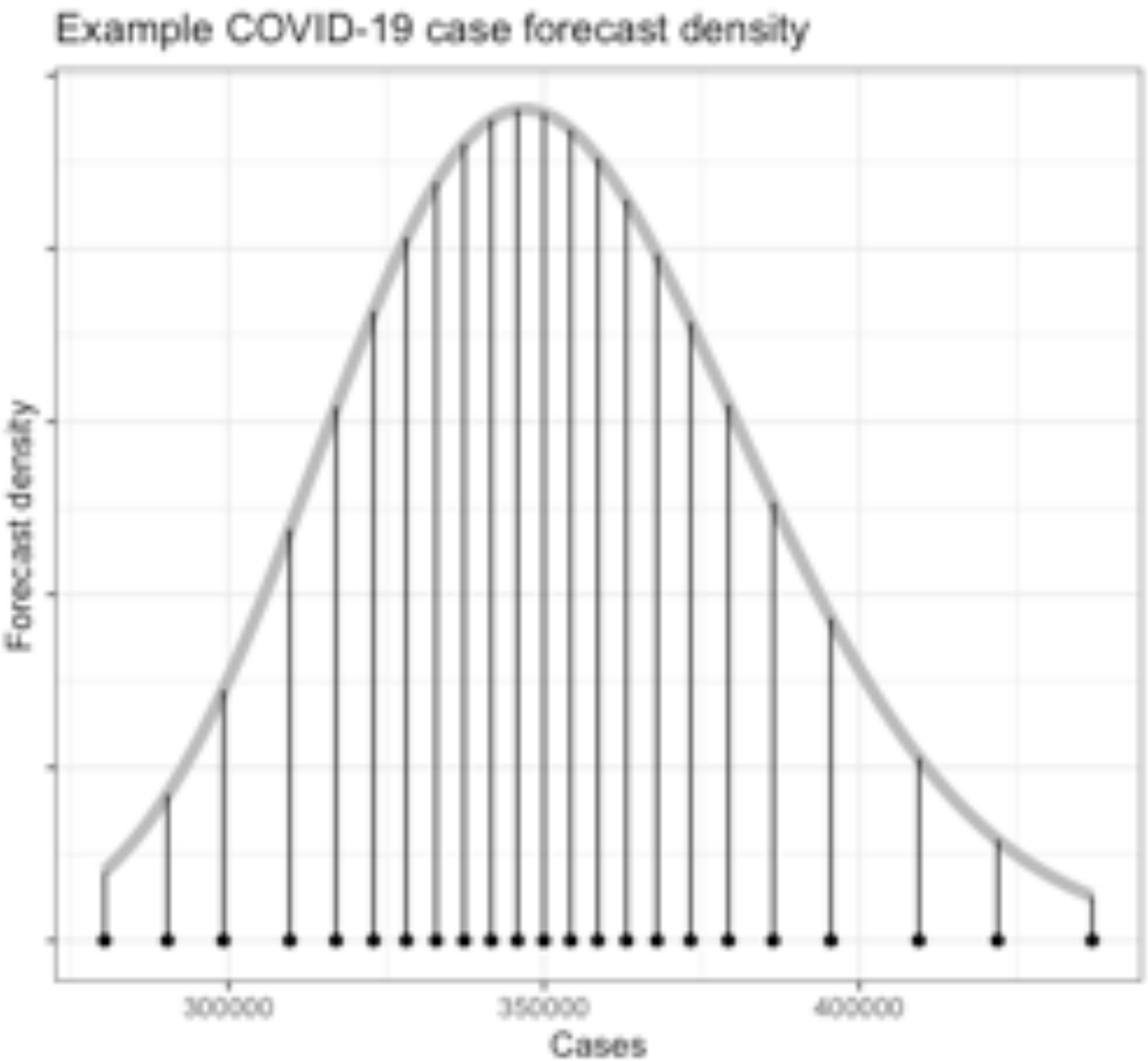
Anti-probabilistic forecasts

Four Different Forecast Evaluation Challenges:

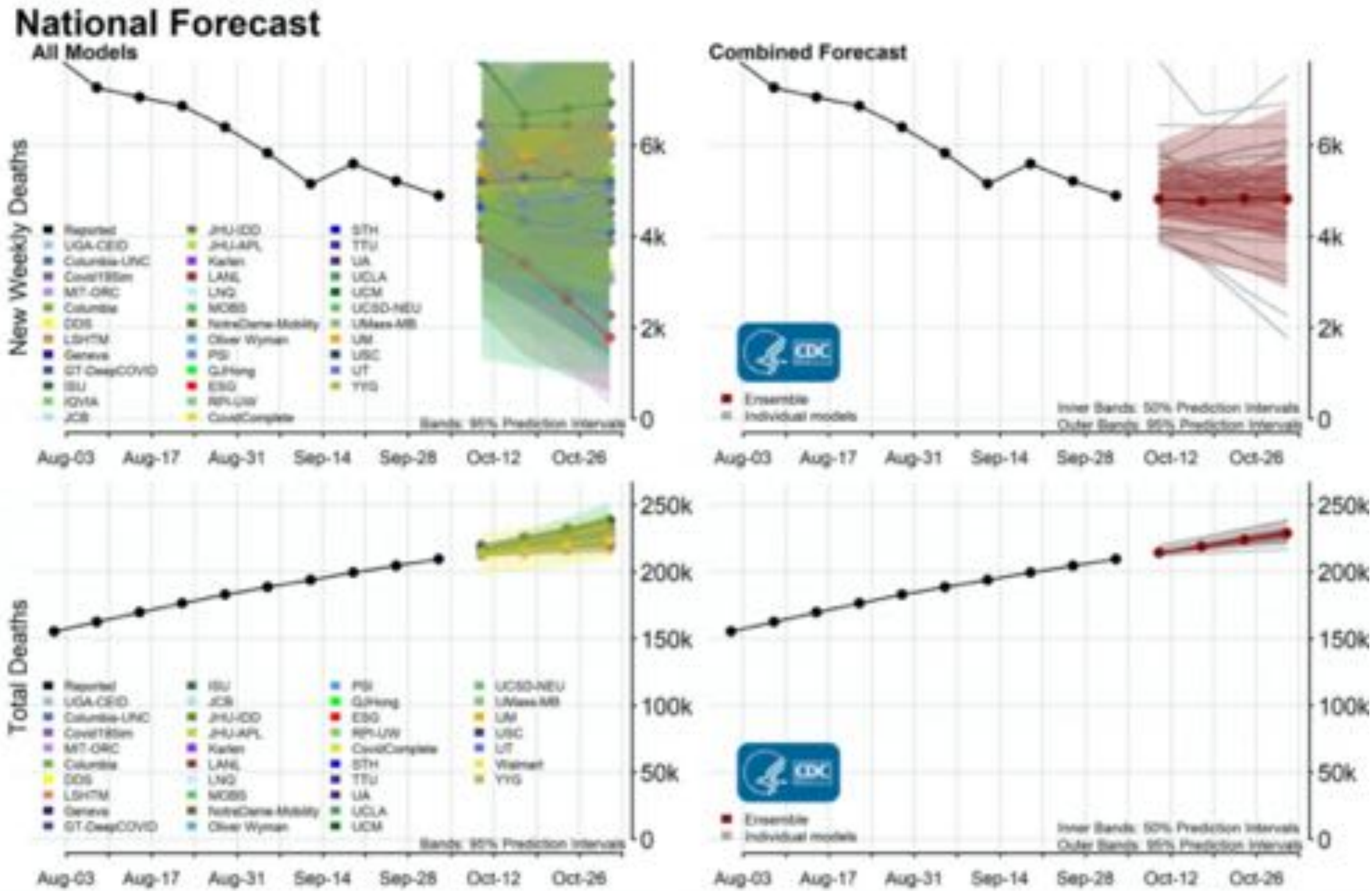
- National Point Forecasts
  - One time series (per model)
  - Excellent accuracy over time
- National Prediction Interval Forecasts
  - Purpose of these is not clear, considering the accuracy of the national point forecasts
- State Point Forecasts
  - 51+ time series (per model)
  - 3 orders of magnitude difference across the time series
- State Prediction Interval Forecasts
  - Purpose of these is clear, considering the (in)accuracy of the point forecasts

Probabilistic COVID-19 Forecasts

```
quantiles = c(0.01, 0.025, seq(0.05, 0.95, by = 0.05), 0.975, 0.99)
```

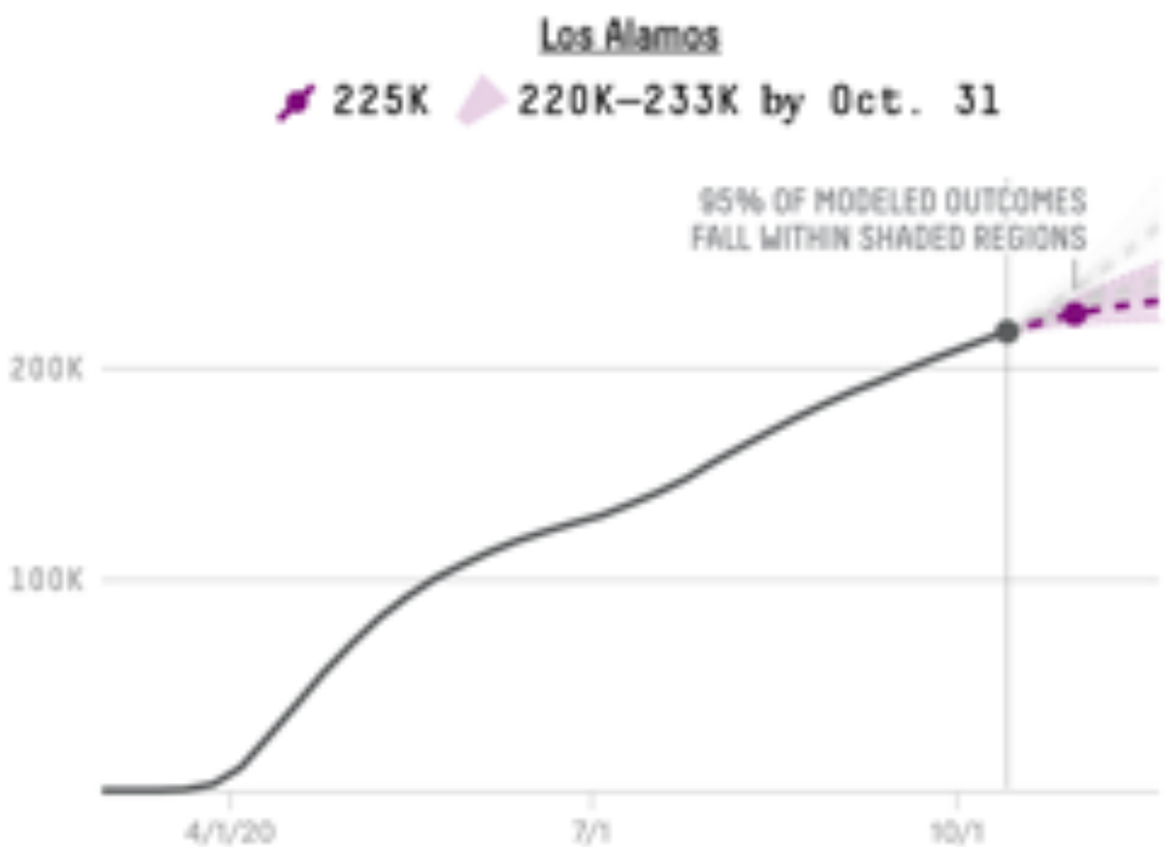


CDC COVID-19 Forecast



538 COVID-19 Forecasts

projects.fivethirtyeight.com/covid-forecasts



This model assumes that there will continue to be interventions, such as stay-at-home orders, but it does not specifically assume what those interventions will be. Instead, it considers various possible interventions to arrive at its forecast, which typically results in wider prediction intervals than a model with stricter assumptions.

This model accounts for state reopenings, and assumes that interventions would be reenacted if cases continue to increase. The model was changed significantly on July 4.

COVID-19 Forecast Questions

Define “forecast date”:

- **Date of the last data used**
- **Date when model computations started**
- **Date when model computations ended**
- **Date when forecast is available**
  - **Relevant for real-time forecasts**

Submission date compared to “forecast date”

- **Same or next day**

COVID-19 Forecast Questions

- **Should models be allowed to revise their forecasts?**
  - **No:**
    - **Modelers need to stand by their work**
    - **Modelers could cheat if allowed to revise**
    - **Downstream forecasts are based on the forecasts received**
    - **Bugs can be consider a part of the modeling effort**
  - **Yes:**
    - **Bugs are inevitable and not representative of the method**
    - **Erroneous forecasts make the Hub look bad**

COVID-19 Forecast Questions

- **Should cumulative and incident forecasts be consistent?**
  - **No:**
    - **No reason modelers should have to use the same model**
    - **Due to data delay and computation time, it is impossible**
  - **Yes:**
    - **Otherwise ensemble won't be consistent**
    - **Modelers should fix their bugs**

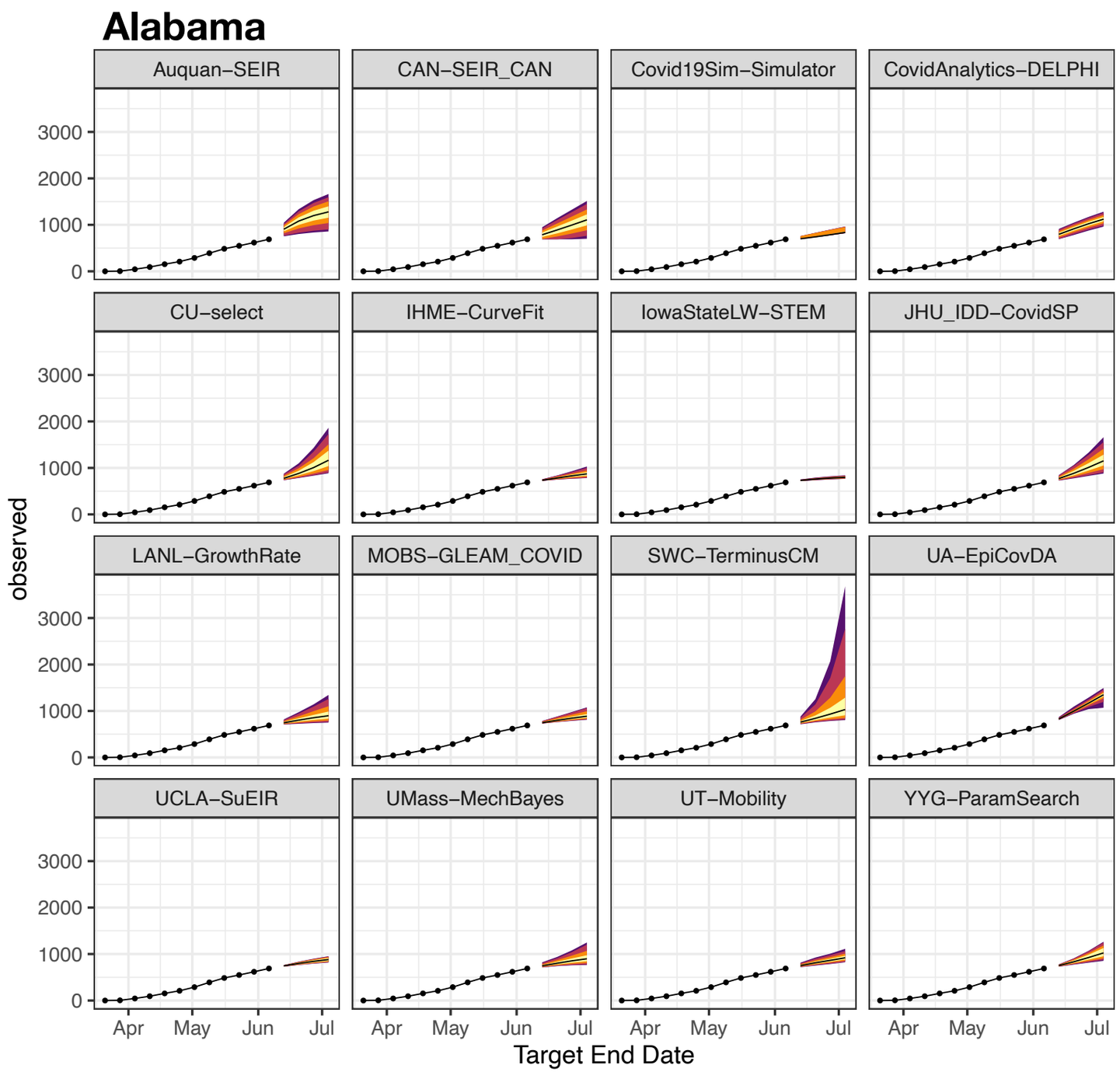
observed_cum	one_week_ahead_cum_forecast	implied_median_inc	actual_median_inc	diff
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
214370	215097.	727.	5257.	-4531.
214370	218830.	4460.	6566.	-2107
214370	218396.	4026.	5347.	-1321.
214370	219117	4747	5660	-913
214370	219070.	4700.	5514.	-814.
214370	220812.	6442.	7253.	-811.
214370	218476	4106	4738	-632
214370	219244	4874	5245	-371
214370	218598	4228	4500	-272
214370	219213	4843	5068	-225
214370	219594	5224	5033	191
214370	219271	4901	5089	-188
214370	217690.	3320.	3463.	-143.
214370	222008	7638	7731	-93
214370	218461.	4091.	4094.	-3.04
214370	218806	4436	4439	-3
214370	219316	4946	4948	-2

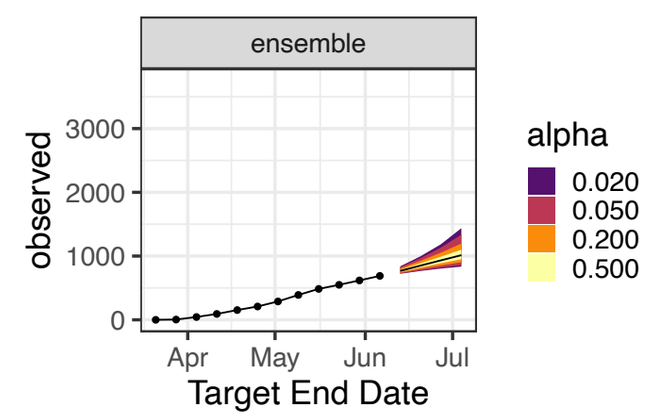
Ensemble construction

COVID-19
ForecastHub

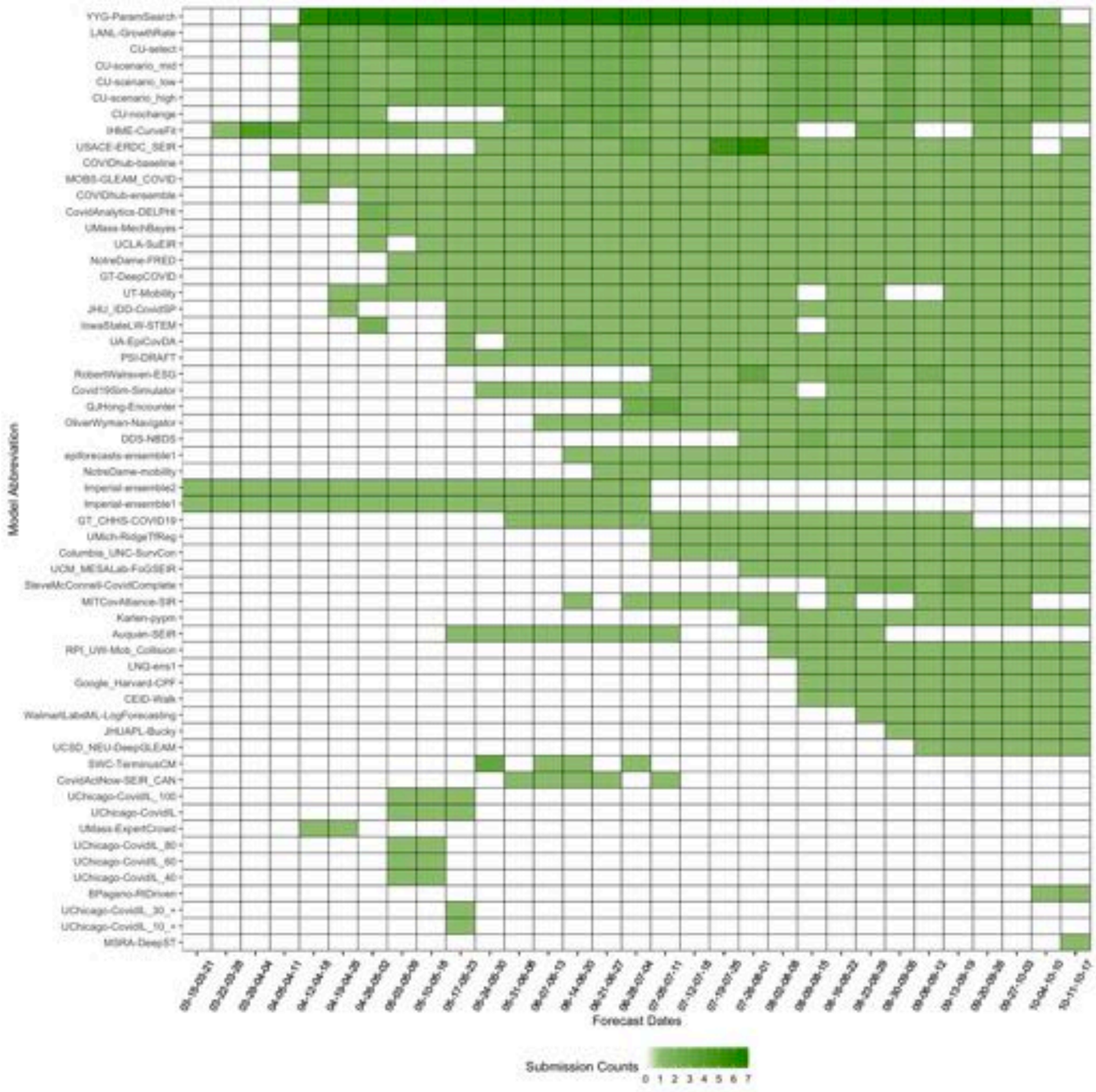
Context and Goals

- Each week we receive forecasts of weekly incident deaths and cumulative deaths due to COVID-19 from approximately 25 teams and 30 models.
- We build an ensemble that combines the predictions from these models.





Models and submissions evolve over time

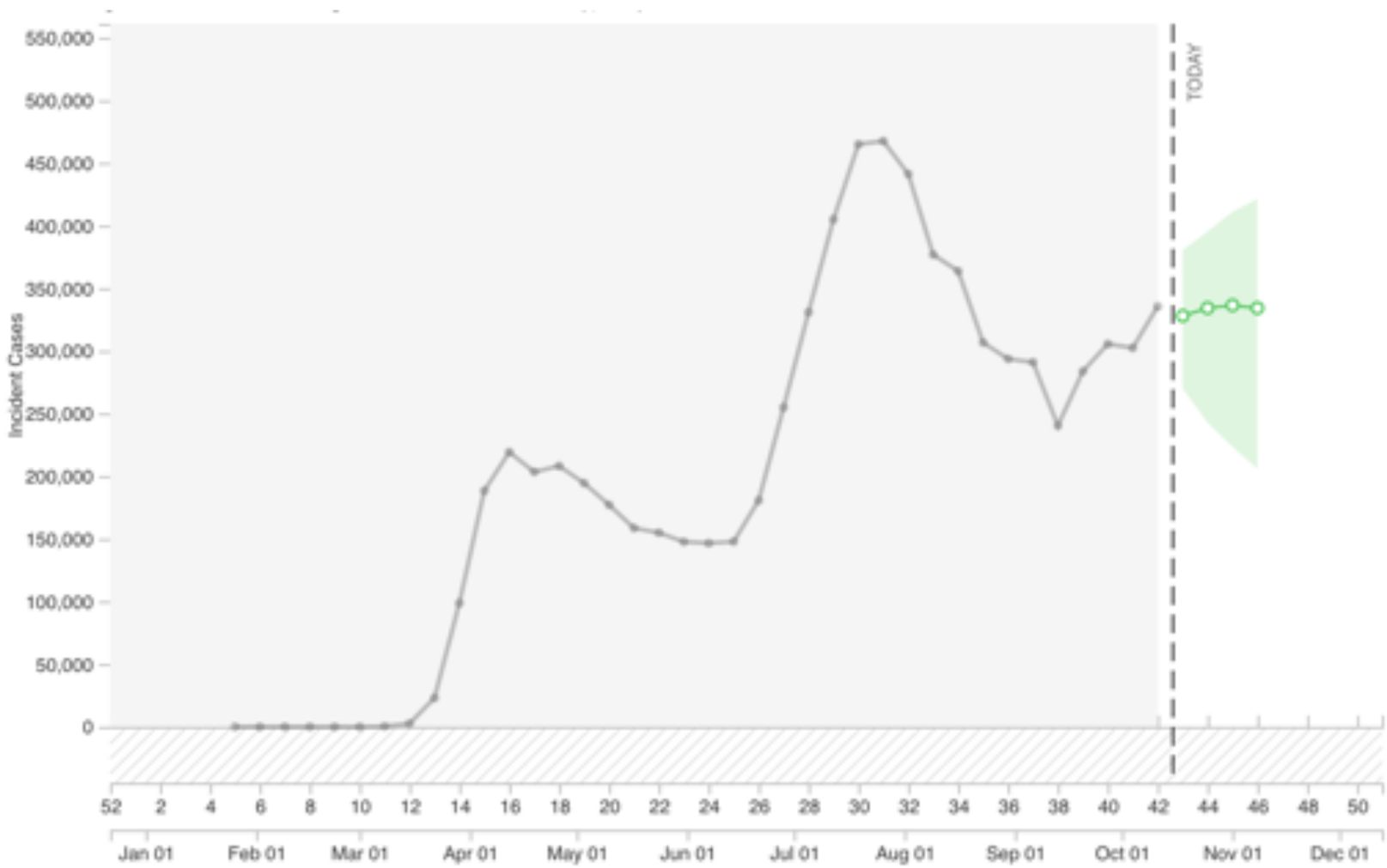


Forecasts collected from models

- Models are required to submit 23 quantiles of a predictive distribution:

$$\widehat{P}(Y \leq q_1) = 0.01,\ \widehat{P}(Y \leq q_2) = 0.025,\ \ldots,\ \widehat{P}(Y \leq q_{23}) = 0.99$$

- Each model provides univariate predictive distributions for a set of "step-ahead" forecast targets, e.g. 1-4 week ahead incident reported deaths in a specific location, as reported by the JHU CSSE COVID-19 dashboard.



Weighted Average of Quantiles

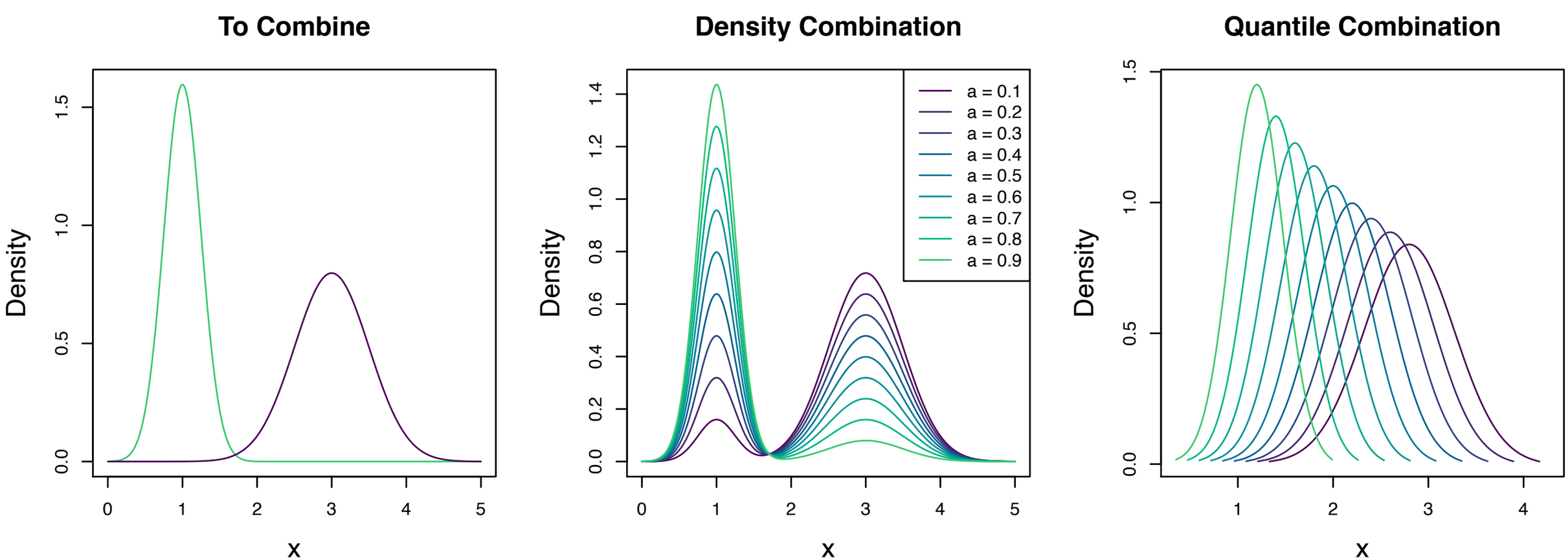
- Models are required to submit 23 quantiles of a predictive distribution:

$$\widehat{P}(Y \leq q_{m,1}) = 0.01,\ \widehat{P}(Y \leq q_{m,2}) = 0.025,\ \ldots,\ \widehat{P}(Y \leq q_{m,23}) = 0.99$$

- At each quantile level, we compute the average across all included models

$$q_k = \sum_{m=1}^{M} w_{m,k}\, q_{m,k},\ k = 1,\ldots,23, \qquad \sum_{m=1}^{M} w_{m,k} = 1, w_{m,k} \geq 0$$

- This is different from computing the average of the predictive density functions (figures adapted from Ryan Tibshirani):



Model evaluation

COVID-19
ForecastHub

Youyang Gu Model Evaluation

covid19-projections.com

Best-performing models for US state-by-state - 4-week ahead forecasts

We take the weekly projections sent to the CDC for all 50 states (+DC), and compare their incident deaths projections for 4 weeks ahead with each state's true reported incident deaths for those 4 weeks. We take the mean of the absolute errors for each state.

Baseline is a simple model where we take the mean of the previous week's daily deaths to make all future forecasts. For example, for July 20 projections, we use the average daily deaths from July 13 to July 19 for all future projections (this is a constant number).

Projections in red = failed to outperform the baseline model of simply using the previous week's average deaths to make all future projections.

Team category: blue = academic institution; purple = private company; orange = government/military; brown = independent

Note: For fair comparisons, we are only considering models that have 3+ submissions.

Source: https://github.com/youyanggu/covid19-forecast-hub-evaluation

Mean absolute error for 4-week ahead forecasts

	4/20 - 5/16	4/27 - 5/23	5/4 - 5/30	5/11 - 6/6	5/18 - 6/13	5/25 - 6/20	6/1 - 6/27	6/1 - 6/27	6/15 - 7/11	6/22 - 7/18	6/29 - 7/25	7/6 - 8/1	7/13 - 8/8	7/20 - 8/15	7/27 - 8/22	8/3 - 8/29	8/10 - 9/5	8/17 - 9/12	8/24 - 9/19	8/31 - 9/26	% weeks beat baseline
COVIDHub Ensemble (combination of various models)		190	105	142	117	122	118	95	87	87	98	175	162	116	111	74	71	53	64	72	100%
YYG - covid19-projections.com	278	233	132	140	172	142	89	99	98	121	138	205	132	140	137	99	80	64	67	70	100%
UMass-MB - University of Massachusetts, Amherst		757	272	122	102	62	145	88	97	150	192	176	121	135	194	134	103	76	94	109	79%
UCLA - University of California, Los Angeles			251	208	107	99	109	120	110	133	193	234	201	200	147	117	105	108	89	89	100%
Oliver Wyman								102	98	139	163	184	180	134	119	100	72	58	69	91	100%
MIT_CovidAnalytics - MIT		259	305	298	244	155	127	168	170	152	183	238	184	150	136	145	129	93	122	121	68%
LANL - Los Alamos National Laboratory	400	318	167	132	129	112	108	100	102	114	160	221	239	254	278	226	161	151	139	132	55%
Baseline (use previous week's average daily deaths)	351	338	290	309	264	207	171	185	162	165	323	265	233	203	153	120	107	124	110	106	---
Covid19Sim - COVID-19 Simulator						176	196	175	119	115	175	203	136	138	132	142	N/A	N/A	156	87	77%
IowaStateLW - Iowa State University		233	321	N/A	153	129	158	130	128	136	231	255	240	207	163	152	N/A	146	172	113	53%
IHME - Institute for Health Metrics and Evaluation	529	552	238	177	194	N/A	174	134	125	92	137	209	N/A	204	170	165	138	N/A	254	233	47%
UA - University of Arizona						295	235	264	152	101	259	270	266	150	117	137	130	119	108	194	47%
USC - University of Southern California											183	253	277	180	190	93	92	77	102	92	80%
LNQ - LockNQuay														125	132	68	86	95	70	67	100%
MOBS - Northeastern University	620	410	461	443	265	155	133	135	148	183	231	256	249	231	227	420	134	114	125	147	35%
UT - University of Texas, Austin	664	549	452	N/A	233	123	106	117	127	136	143	229	181	247	454	616	N/A	284	125	N/A	53%
COVIDHub Baseline	686	332	289	372	274	241	184	175	180	182	343	275	261	220	161	151	114	144	139	129	---
CMU - Carnegie Mellon University (Delphi)														156	138	82	125	73	91	57	86%
CU-select - Columbia University	427	325	221	209	228	208	332	313	271	480	709	293	170	210	225	184	130	171	136	155	25%
JCB - John Burant															113	111	85	74	81	74	100%
USACE - US Army Engineer Research and Development Center					248	194	258	209	121	148	244	165	173	519	321	297	253	229	207	208	44%
GT-DeepCOVID - Georgia Institute of Technology												302	285	240	199	165	141	106	94	129	22%
NotreDame-mobility - University of Notre Dame										264	441	286	242	237	271	329	269	155	132	111	0%
JHU_IDD - Johns Hopkins University					1108	432	382	378	228	274	264	281	244	257	238	240	240	255	160	135	6%
PSI - Predictive Science Inc					332	209	152	168	206	246	272	362	371	229	467	737	270	298	169	157	13%
Auquan - Auquan Data Science					347	365	368	761	836	151	209	308	N/A	N/A	N/A	205	142	151	158	N/A	15%
Karlen - Karlen Working Group														834	393	323	207	166	132	99	14%
CEID - University of Georgia																	106	140	132	125	0%
DDS - Discrete Dynamical Systems															776	390	946	183	162	82	17%
Robert Walraven												476	486	1787	267	187	670	185	189	164	0%
EpiForecasts - LSHTM																		110	133	150	0%
MITCovAlliance - MIT											304	471	555	458	456	341	N/A	440	N/A	N/A	14%
Median Mean Abs Error	*478*	*328*	*272*	*208*	*233*	*166*	*158*	*151*	*127*	*148*	*209*	*255*	*239*	*207*	*190*	*158*	*129*	*132*	*125*	*113*	

Weighted Interval Score

- Consider a single $(1-\alpha)\times 100\,\%$ predictive interval [l, u] for the observed response y. The interval score is:

$$\textbf{IS}_\alpha(F,y) = \underbrace{(u-l)}_{\text{Width of interval}} + \frac{2}{\alpha}\cdot\underbrace{(l-y)\cdot\mathbf{1}(y<l)}_{\text{Penalty if interval is too high}} + \frac{2}{\alpha}\cdot\underbrace{(y-u)\cdot\mathbf{1}(y>u)}_{\text{Penalty if interval is too low}},$$

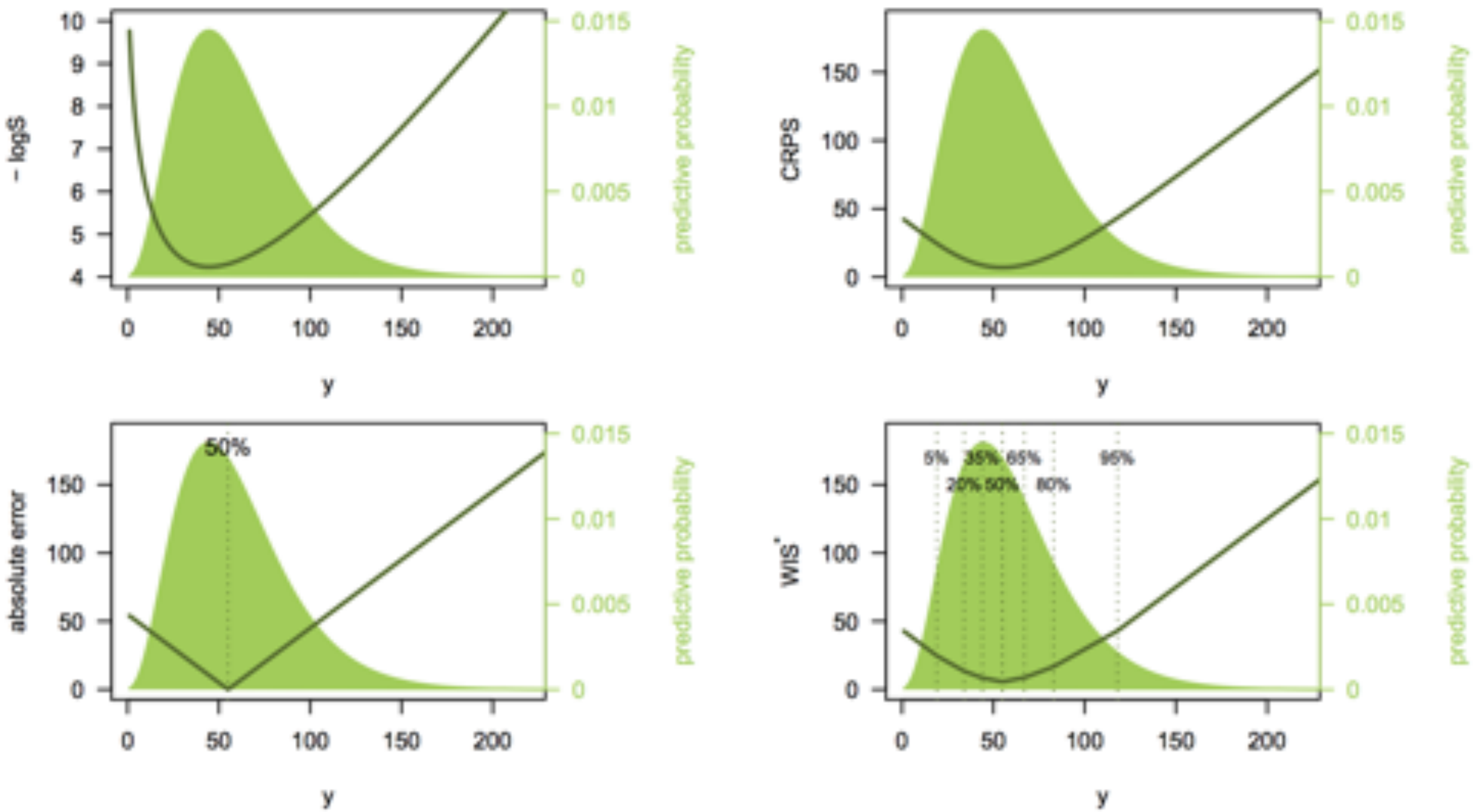
- Smaller $\textbf{IS}_\alpha$ is better
- For multiple predictive intervals, we compute a weighted average of $\textbf{IS}_\alpha$

$$\textbf{WIS}_{\alpha_{0:K}}(F,y) = \frac{1}{K+1}\times\left(w_0\times 2\times|y-m| + \sum_{k=1}^{K}\left(w_k\times\textbf{IS}_{\alpha_k}(F,y)\right)\right).$$

- We use weights $w_i = \frac{\alpha_i}{2}$

- The resulting score is **proper** — forecasters don't have any incentive to report anything other than their true beliefs about the future.
- See Bracher et al. (2020) for more: https://arxiv.org/abs/2005.12881

WIS compared to other scores



Examples of log score (negatively oriented), continuous ranked probability score (CRPS), absolute error, and the weighted interval score (WIS). Scores are shown as a function of the observed value y. The predictive distribution is Negative Binomial with mean 60 and size 4.

For all scores as shown, smaller values are desirable.

General Quantile Combinations

- General set up:

$$q_k = \beta_{0,k} + \sum_{m=1}^{M} \beta_{m,k} q_{m,k}, \; k = 1,\ldots,23$$

k'th predictive quantile for ensemble

k'th predictive quantile for component model number m

- Equally weighted has $\beta_{0,k} = 0$ and $\beta_{m,k} = \frac{1}{M}$
- Estimate parameters by minimizing the Weighted Interval Score achieved by the ensemble in a window of recent weeks subject to some constraints.

Practical challenges

- **Missingness**: not every model makes forecasts at each location or in every week
- **Window size:** How many past weeks of performance are used to estimate model weights? 1, 2, 3, or 4; also, 0 for Equal Weighted
- **Constraints** on parameters

Comparing Ensemble specifications

averaging across 4 targets, all locations

Mean WIS, COVIDhub-ensemble (our actual real-time ensemble forecast): 61.14859

Mean WIS, YYG-ParamSearch (a top performing individual model): 64.94579

Comparing Ensemble specifications

averaging across 4 targets, all locations

Mean WIS, COVIDhub-ensemble (our actual real-time ensemble forecast): 61.14859
Mean WIS, YYG-ParamSearch (a top performing individual model): 64.94579

missingness <chr>	constraint <chr>	quantile group <chr>	window <int>	checks <chr>	mean_wis <dbl>
per location group	equal	per model	3	standard	57.15831
per location group	convex	per quantile	4	standard	57.28399
per location group	convex	3 groups	4	baseline	58.44847
per location group	equal	per model	4	standard	58.80845
per location group	convex	per model	4	standard	59.79603
per location group	convex	3 groups	4	standard	59.92877
impute	convex	per quantile	2	none	60.08238
impute	convex	per quantile	3	standard	60.29250
impute	convex	per quantile	2	standard	60.61362
per location group	equal	per model	0	standard	82.49395

Top approaches have comparable error to our equal-weighted approach.

Comparing Ensemble specifications

averaging across 4 targets, all locations

Mean WIS, COVIDhub-ensemble (our actual real-time ensemble forecast): 61.14859
Mean WIS, YYG-ParamSearch (a top performing individual model): 64.94579

missingness <chr>	constraint <chr>	quantile group <chr>	window <int>	checks <chr>	mean_wis <dbl>
per location group	equal	per model	3	standard	57.15831
per location group	convex	per quantile	4	standard	57.28399
per location group	convex	3 groups	4	baseline	58.44847
per location group	equal	per model	4	standard	58.80845
per location group	convex	per model	4	standard	59.79603
per location group	convex	3 groups	4	standard	59.92877
impute	convex	per quantile	2	none	60.08238
impute	convex	per quantile	3	standard	60.29250
impute	convex	per quantile	2	standard	60.61362
per location group	equal	per model	0	standard	82.49395

Top-ranked approaches require submission history and drop models that fail automated checks

Comparing Ensemble specifications

averaging across 4 targets, all locations

Mean WIS, COVIDhub-ensemble (our actual real-time ensemble forecast): 61.14859
Mean WIS, YYG-ParamSearch (a top performing individual model): 64.94579

missingness <chr>	constraint <chr>	quantile group <chr>	window <int>	checks <chr>	mean_wis <dbl>
per location group	equal	per model	3	standard	57.15831
per location group	convex	per quantile	4	standard	57.28399
per location group	convex	3 groups	4	baseline	58.44847
per location group	equal	per model	4	standard	58.80845
per location group	convex	per model	4	standard	59.79603
per location group	convex	3 groups	4	standard	59.92877
impute	convex	per quantile	2	none	60.08238
impute	convex	per quantile	3	standard	60.29250
impute	convex	per quantile	2	standard	60.61362
per location group	equal	per model	0	standard	82.49395

COVIDhub-ensemble if we didn't manually eliminate models based on visual mis-alignment --> human-in-the-loop has helped.

Comparing Ensemble specifications

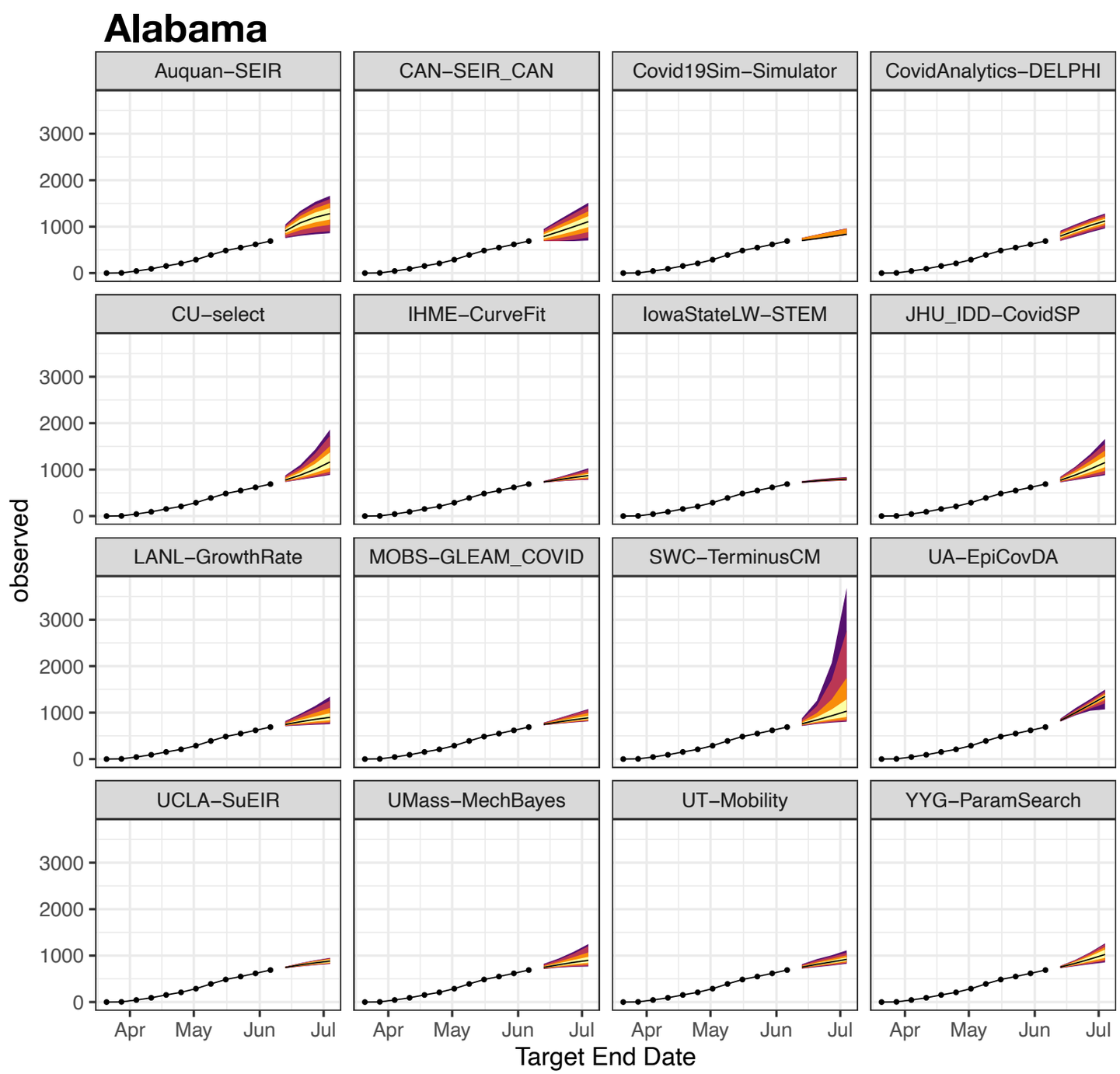
averaging across 4 targets, all locations

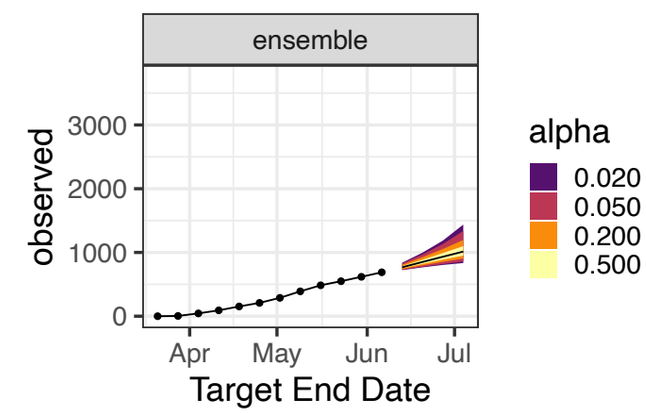
Mean WIS, COVIDhub-ensemble (our actual real-time ensemble forecast): 61.14859
Mean WIS, YYG-ParamSearch (a top performing individual model): 64.94579

missingness <chr>	constraint <chr>	quantile group <chr>	window <int>	checks <chr>	mean_wis <dbl>
per location group	equal	per model	3	standard	57.15831
per location group	convex	per quantile	4	standard	57.28399
per location group	convex	3 groups	4	baseline	58.44847
per location group	equal	per model	4	standard	58.80845
per location group	convex	per model	4	standard	59.79603
per location group	convex	3 groups	4	standard	59.92877
impute	convex	per quantile	2	none	60.08238
impute	convex	per quantile	3	standard	60.29250
impute	convex	per quantile	2	standard	60.61362
per location group	equal	per model	0	standard	82.49395

In recent weeks, approaches that rely only on estimation to remove models have started to show competitive performance. (This was not true early on.)
Note: still not much better than our current approach

Result in Pictures





VERY preliminary accuracy results

- Nearly all submitted models **do not beat** baseline model.
- COVID-19 Forecast Hub ensemble
  - is one of a few models that consistently outperforms the baseline
  - has approximately nominal coverage for death forecasts
  - has lower than nominal coverage for case forecasts

Next steps

- Continued crank-turning on collection and aggregation of short-term forecasts for national and state levels.
- Collecting county-level forecasts of cases, in hopes of informing COVID-19 vaccine site selection efforts.
- With funding and collaborative support from CDC, we will continue to use statistical approaches to make accurate short-term forecasts of where this pandemic is taking us.

COVID-19 ForecastHub

www.medrxiv.org/content/10.1101/2020.08.19.20177493v1

Ensemble Forecasts of Coronavirus Disease 2019 (COVID-19) in the U.S.

Evan L Ray, Nutcha Wattanachit, Jarad Niemi, Abdul Hannan Kanji, Katie House, Estee Y Cramer, Johannes Bracher, Andrew Zheng, Teresa K Yamana, Xinyue Xiong, Spencer Woody, Yuanjia Wang, Lily Wang, Robert L Walraven, Vishal Tomar, Katherine Sherratt, Daniel Sheldon, Robert C Reiner, B. Aditya Prakash, Dave Osthus, Michael Lingzhi Li, Elizabeth C Lee, Ugur Koyluoglu, Pinar Keskinocak, Youyang Gu, Quanquan Gu, Glover E George, Guido España, Sabrina Corsetti, Jagpreet Chhatwal, Sean Cavany, Hannah Biegel, Michal Ben-Nun, Jo Walker, Rachel Slayton, Velma Lopez, Matthew Biggerstaff, Michael A Johansson, Nicholas G Reich, COVID-19 Forecast Hub Consortium

doi: https://doi.org/10.1101/2020.08.19.20177493

Questions?

covid19forecasthub.org

jarad.me

Slides modified from the Hub team particularly Evan Ray and Nick Reich