Methodological factors in forecast performance: the influence of model structure and target specificity on the performance of real time COVID-19 forecasts [provisional title]

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#### Abstract

Performance of forecasts in capturing observed data varies in time and space with no overall "best" forecast. Two varying features of forecasting methods include the forecaster's approach to model structure; and whether the forecaster tunes their model to each target. We investigate forecasts of weekly incident deaths for 32 countries submitted to the European COVID-19 Forecast Hub between March 2021 and March 2023.

We use teams' provided metadata to categorise models by their structure (mechanistic, semi-mechanistic, statistical), and by their specificity (the number of locations each team targets; and whether the target location is the same as the team's institutional location, as a proxy for adaptation of model parameters to local conditions). We evaluate forecasts using the weighted interval score, scaled relative to a baseline of the median ensemble of all models.

# Background

COVID-19 deaths in Europe, with respect to the long-term factors of model structure and target specificity.  Forecast performance is variable between models. Variable performance among forecasts is useful for both interpreting forecast outputs among different models, and learning how to improve forecast models and interpretation in the future.
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models and interpretation in the future.
However, it is unclear how to prioritise learning from forecast outputs in
the short term (for both forecast creators and interpreters), without an
understanding of whether and which features of the underlying forecast
models may be associated with variable performance.
Two long term (persistent) features of forecasting methods include (in a
very simplified way) the forecaster's approach to:
Model structure – on a spectrum of deterministic, to     probabilistic
Target specificity - fitting or adapting model parameters to the
specific conditions of each target, on a spectrum from using
only pre-specified data as published, to using only individual judgement
We investigate whether these factors make some contribution to
variance in performance.
We focus only on deaths to allow for the aim of exploring target
specificity as variation across countries, rather than
countries-by-variable. Deaths is the more reliable forecast target
between countries (re. data) and where the individual models make the
most difference (vs. ensemble).
Model structure: some recent COVID-19 hub comparisons - Ray,
Bracher; previous work
Target specificity: builds on expert judgement work

Relevance of	Need for this work
new work	Large scale of hub; using standardised forecasts - only
	possible to explore variation among teams and their
	models while keeping methods, targets, horizons,
	variables constant
	Target specificity - able to assess across many countries
	with comparable data
	Relevance
	<ul> <li>To individual modellers: areas of focus for</li> </ul>
	methodological development
	<ul> <li>To future large multi-model comparison projects:</li> </ul>
	encouraging methodological diversity, use of
	methodological background in communicating results
Research	Assess the range of performance by individual models over time
questions	Classify models' methodological structure and investigate
	whether this influences forecast performance
	Explore differences in performance by whether teams are
	forecasting for one or more countries (is a model that's
	"good/bad" overall good/bad everywhere?); including
	performance by whether teams are forecasting the country in
	which they are located

## Methods

Setting	Euro hub
Unit of analysis	Quantile forecasts of weekly incident counts of COVID-19 deaths per country, for any combination of givens: location (32), target date (1-4 week horizon by week)
Sample	<ul> <li>Inclusion</li> <li>Submitted quantile forecasts over period 8 March 2021 -         10 March 2023</li> <li>Model metadata includes methods or linked citation</li> </ul>

	Exclusions
	o ? Point-only forecasts without quantiles
	o Anomalies: models designated "other"; forecasts made
	after major data anomalies
Procedure	1. Classifying forecasts
(codebase)	Model structure
	o Qualitatively define from teams' own descriptions of
	methods section in metadata or citation
	o Each model = one of {mechanistic, semi-mechanistic,
	statistical}. Possibly: spatial; ML; "other"
	Target specificity
	o Count total (ever) target locations per model
	o Each model = single-target or multiple-target. Possibly:
	few-target i.e. <=3 targets
	o Categorise team location: qualitatively categorise "home"
	location using location of team institution, either as given
	or if missing, the institution of the first contributor in
	metadata
	o Each model-target pair = "home" / "foreign"
	2. Forecast evaluation
	Scoring relative to baseline as unweighted median ensemble of
	all models
	Take all included forecasts, add variables for model structure and
	location of team relative to target location
	Use log scoring to help account for varying importance of error
	over time

## Results

Setting	<ul> <li>Shape of epidemic across Europe over time</li> </ul>
	<ul> <li>Performance of baseline ensemble</li> </ul>
	<ul> <li>Overall trends in forecast performance by horizon / target</li> </ul>

Sample size &	Number of models
characteristics	Model structure
	<ul> <li>Target specificity: multi-target models, single-target models;</li> </ul>
	models targeting home/foreign location
	<ul> <li>Overlap between structure &amp; specificity: e.g. perhaps all</li> </ul>
	statistical models are single-target models, etc
Forecast	<ul> <li>Focus on relative WIS, scaled against baseline; include MAE for</li> </ul>
evaluation	point forecasts
	<ul> <li>Analysis grouped by (at minimum) horizon, the category of</li> </ul>
	model structure and target specificity. Possibly by: variable, time
	period (epidemic phase / variant)
	Simple comparisons among scores by group (possibly, model:
	WIS ~ structure + location ; possibly with interaction)

#### Discussion

Methods: issues, mitigations  Sampling  Model structure o Model structure as continuum of structured/unstructured, iterative (mathematical-statistical) o Methods classified into model structures as described in metadata, not verified against code	Summary of	
issues, mitigations  • Model structure  • Model structure as continuum of structured/unstructured, iterative  (mathematical-statistical)  • Methods classified into model structures as described in metadata,	key results	
<ul> <li>o No independent secondary verification of model structure / location</li> <li>o No account of changing methods (leading to shift in model structure) over time</li> <li>Target specificity</li> <li>o Team institute location a poor proxy for individual model contributors' knowledge of epidemic in target location</li> </ul>	issues,	<ul> <li>Model structure</li> <li>Model structure as continuum of structured/unstructured, iterative (mathematical-statistical)</li> <li>Methods classified into model structures as described in metadata, not verified against code</li> <li>No independent secondary verification of model structure / location</li> <li>No account of changing methods (leading to shift in model structure) over time</li> <li>Target specificity</li> <li>Team institute location a poor proxy for individual model</li> </ul>

o Location sample size – 34 teams but relatively few location/target pairs (7 Euro countries, not all teams forecasting within/outside team location) **Evaluation** Use of relative scoring to an ensemble, rather than alternative baseline of flat-line forecast as in previous work. (But could be inappropriate to use a statistical baseline to evaluate a mathematical model?) No uncertainty in model scoring Data inputs – evaluation against JHU data, but teams may use different data for model inputs, meaning evaluation against JHU data may be inappropriate (?). Data inputs likely affected by team location. Mitigation: teams knew evaluation would be against JHU data **Confounders** Modellers' ability to adapt parameters to changing local conditions interacts with model structure. But we only have very limited information on either factor of structure or parameters so likely difficult to explore this in much depth. Conclusions / weight of evidence Recommendati Improvements / future work Better classification of qualitative adaptation of model to targets ons Interaction of structural (long term) factors with stochastic (short term/real time, external) events during epidemic: Identifying model responsiveness to data issues; or during epidemic phase (rising, steady, decline)