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On the multibin logarithmic score used in the FluSight competitions

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This is a preprint of a letter published in PNAS (https://doi.org/10.1073/pnas.1912147116). In their reply, Reich et al. (https://doi.org/10.1073/pnas.1912694116) discuss the usefulness of different scoring rules in a public health context.

The FluSight challenges [9] represent an outstanding collaborative effort and have “pioneered infectious disease forecasting in a formal way” [10]. However, I would like to initiate a discussion about the employed evaluation measure.

The competitions feature discrete or discretized targets related to the US influenza season. E.g. for the peak timing $Y$, a forecast distribution $F$ consists of probabilities $p_1, \ldots, p_T$ for the $T = 33$ weeks of the season. Such forecasts can be evaluated using the log score [2, 3]

$$\logS(F, y_{\text{obs}}) = \log(p_{y_{\text{obs}}})$$

where $y_{\text{obs}}$ is the observed value. This score is strictly proper, i.e., its expectation is uniquely maximized by the true distribution of $Y$. In the FluSight competitions the logS is applied in a multibin version,

$$\text{MBlogS}(F, y_{\text{obs}}) = \log\left(\sum_{i=1}^{d} p_{y_{\text{obs}}+i}\right),$$

to measure accuracy of practical significance [9]. Depending on the target, $d$ is either 1 or 5. Following the competitions, this score has become widely used [1, 5, 4, 6, 8, 7], even though as also mentioned in [9], it is improper. This may be problematic as improper scores incentivize dishonest forecasts. Assume $T > 2d$ and

$$p_1 = \cdots = p_d = p_{T-d+1} = \cdots = p_T = 0,$$

i.e., zero probabilities for the $2d$ extreme categories. Now define a blurred distribution $\tilde{F}$ with

$$\hat{p}_t = \frac{\sum_{i=-d}^{d} p_{t+i}}{2d+1}, t = 1, \ldots, T,$$

where $p_t = 0$ for $t < 1$ and $t > T$ and (1) ensures $\sum_{t=1}^{T} \hat{p}_t = 1$. This implies

$$\text{MBlogS}(F, y_{\text{obs}}) = \logS(\tilde{F}, y_{\text{obs}}) + \log(2d+1),$$

i.e., the MBlogS is essentially the logS applied to a blurred version of $F$. To optimize the expected MBlogS under her true belief $F$, a forecaster should therefore not report $F$, but a sharper forecast $G$ so that the blurred
version $\tilde{G}$ (with $\tilde{p}_{G,1}, \ldots, \tilde{p}_{G,T}$ derived from $p_{G,1}, \ldots, p_{G,T}$ as in (2)) is close or equal to $F$. This follows from the propriety of the logS. An optimal $G$ is found by maximizing $\sum_{t=1}^{T} p_t \cdot \log(\tilde{p}_{G,t})$ with respect to $p_{G,1}, \ldots, p_{G,T}$.

This optimal $G$ can differ considerably from the original $F$, as Fig. 1 shows for forecasts of the 2016/17 peak timing by the LANL team [8] (downloaded from https://github.com/FluSightNetwork/cdc-flusight-ensemble/). The optimized $G$ (with $d = 1$) often have their mode shifted by one week and tend to be multimodal, even for unimodal $F$. Averaged over the 2016/17 season they yield improved MBlogS for the peak timing ($-0.434$ vs. $-0.484$). This illustrates that the MBlogS may be gamed, even though we strongly doubt participants have tried so. The logS, like any other proper score, could avoid such pitfalls.

Figure 1: Forecasts $F$ for the peak week, submitted by the LANL team in weeks 6–7, 2017, and optimized versions $G$. Diamonds mark the observed peak week. Expected scores are computed under $F$.

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