Adaptively stacked ensembles for influenza forecasting with incomplete data

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Introduction

Seasonal Influenza infects an average 30 million people in the United States every year[1], overburdening hospitals during weeks of peak incidence. Named by the CDC as an important tool to fight the damaging effects of these epidemics, accurate forecasts of influenza and influenza like illness (ILI) forewarn public health officials about when, and where, seasonal influenza outbreaks will hit hardest.

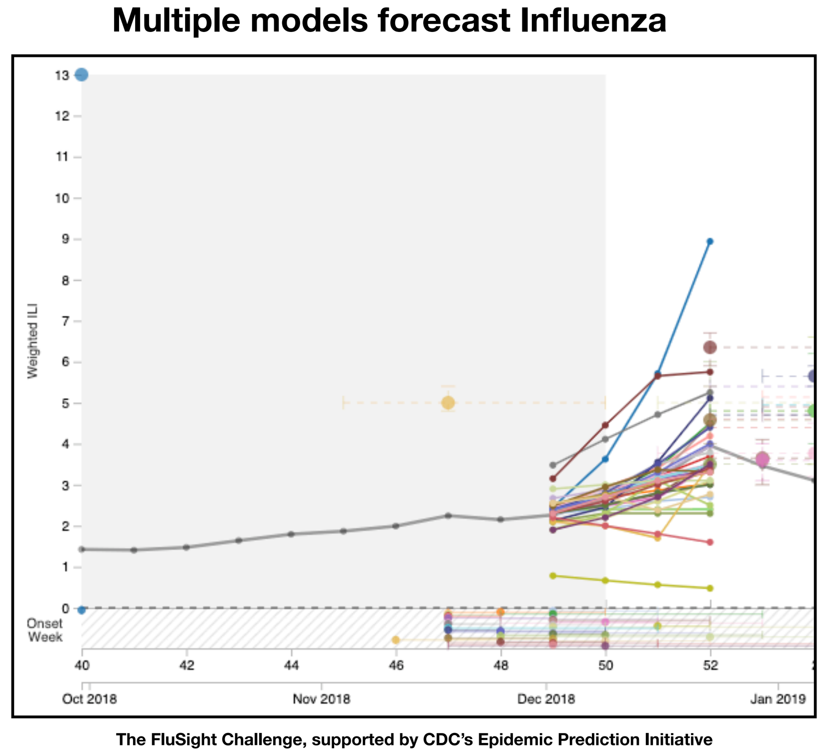
Extending an existing ensemble implementation[2], we developed a new method for combining component models that relies on recently observed, in-season data to adaptively estimate a convex combination of models.

To protect the adaptive ensemble framework from relying too heavily on recent, revision-prone ILI data, we developed a Bayesian model that uses a time-dependent prior to regularize ensemble weights.

Data

Every week throughout the season, for 10 different reporting regions and a national average, the CDC publishes surveillance data on influenza-like illness (ILI). ILI is defined as the percentage of patients presenting with a fever~(greater than 100F) plus cough or sore throat with no known cause other than influenza.

Multiple models forecast Influenza



The FluSight Challenge, supported by CDC's Epidemic Prediction Initiative

21 Component model forecasts

Real-time forecasts from 2010/2011 to present

The FluSight Network (FSN) is a collaborative group of influenza forecasters, using historical performance of models to build ensemble forecasts.

Methods

Assume ILI data is generated by a mixture of component models

$$p(\text{ILI}_t|\pi) = \sum_{m=1}^{\#\text{models}} \pi(m) f(m, \text{ILI}_t)$$

For every epiweek, add a hidden variable that indicates which model generated the t^th ILI value

complete likelihood $$p(\mathcal{D}|\pi, Z) = \prod_{t=1}^{T} \prod_{m=1}^{M} \left[\pi(m) f(m, i_t)\right]^{z(m,t)}$$

Prior is time-dependent

$$p[\pi(t)] = \text{Dir}\left[\pi|\alpha(t)\right] = \frac{\Gamma\left[\sum \alpha(m,t)\right]}{\prod \Gamma\left[\alpha(m,t)\right]} \prod_{m=1}^{M} \pi(m)^{\alpha(m,t)-1}$$

$$\alpha(t) = \frac{\rho N(t)}{M}$$

MAP is a convex combination btw prior and MLE

$$\text{MAP}\left[\pi(m)\right] = \left[\frac{\alpha_m(t)}{\sum_m \alpha_m(t)}\right]\left(\frac{\rho}{1+\rho}\right) + \left(\frac{1}{1+\rho}\right)\left[\frac{\sum_{t=1}^{T} r(m,t)}{N(t)}\right]$$

$r(m,t) =$ responsibility $\rho =$ Percent towards equal weighting

Variational algorithm includes EM as a special case

Algorithm 1 deEM-MM Algorithm

```
input: i_{1×T}, π_0
output: π

ℓℓ ← []
π_{M×1} = π_0
for j=1:maxIters do
    Z_{M×T} ← π × f(i)
    Z ← Z/colSum(Z)
    π ← rowSum(Z)
    π ← π/ sum(π)
    ℓℓ[j] ← computeLL(i,π)
    if LL[j] - LL[j-1] < τ then
        break
    end if
    return π
end for
```

Algorithm 2 deVI-MM Algorithm

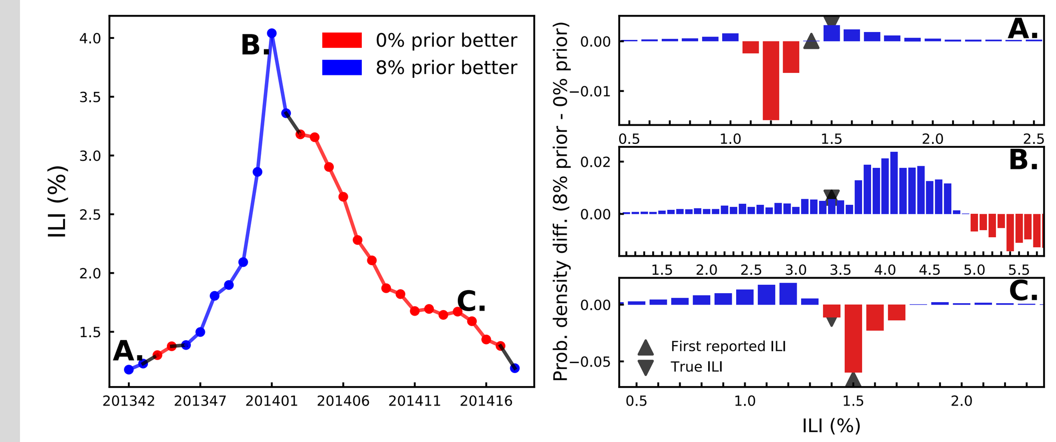
```
input: i_{1×T}, π_0, α_{M×1}
output: π

ELBO ← []
π_{M×1} = π_0
for j=1:maxIters do
    Z_{M×T} ← exp(E(log π) + log f(i))
    Z ← Z/colSum(Z)
    π ← rowSum(Z)
    π ← π/ sum(π) + α
    ELBO[j] ← computeELBO(i,π)
    if ELBO[j] - ELBO[j-1] < τ then
        break
    end if
    return π
end for
```

	2011/2012	2012/2013	2013/2014	2014/2015	2015/2016	2016/2017	2017/2018	Overall
FSN EW	-2.85	-3.22	-2.98	-3.00	-2.99	-3.13	-3.68	-3.09
FSN dynamic (prior=10%)	-2.70	-3.15	-2.88	-2.86	-2.84	-3.01	-3.46	-2.96
FSN dynamic (prior=8%)	-2.70	-3.15	-2.88	-2.85	-2.84	-3.01	-3.46	-2.96
FSN static (prior=10%)	-2.68	-3.06	-2.85	-2.87	-2.82	-2.95	-3.55	-2.94
FSN static (prior=8%)	-2.68	-3.06	-2.84	-2.87	-2.82	-2.95	-3.55	-2.93

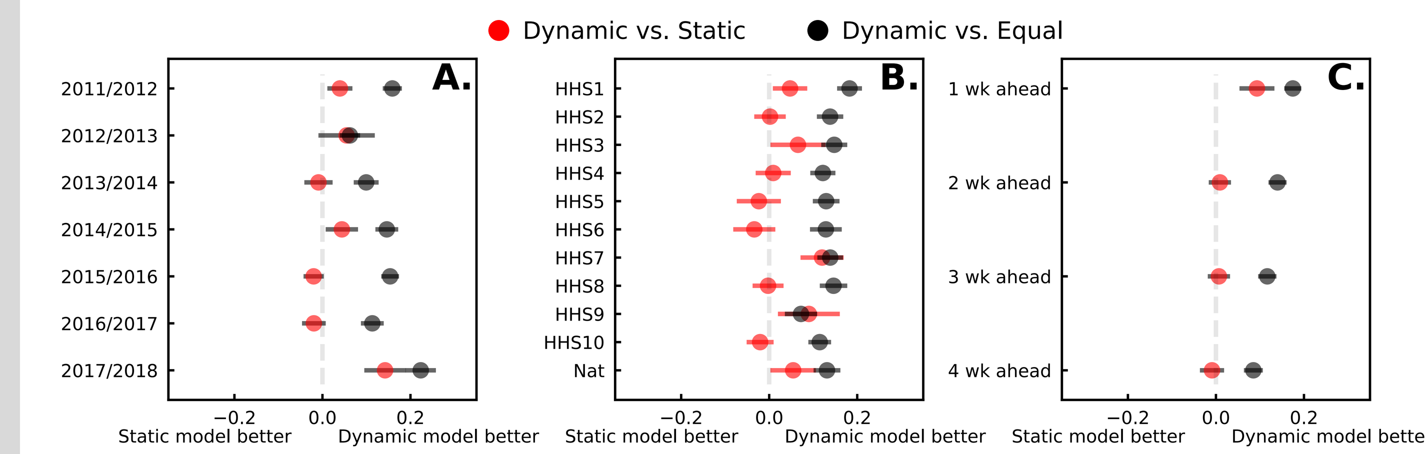
Colour scale: -2.8, -3.0, -3.2, -3.4, -3.6

Adaptive ensemble outperforms Equal-weight

Adaptive ensemble performs similar to static



Knowing data is prone to revision, the prior balances btw a data-driven vs equal weighting



Rslts by Season Region Target

Discussion

Our adaptive ensemble can forecast from revision-prone, noisy ILI data by relying on a prior. We show this adaptive algorithm outperforms an Equal-weight ensemble and shows similar, or better performance against a static ensemble.

Able to generate quick forecasts from sparse or noisy data, an adaptive ensemble could serve as a valuable tool to public health officials, needing to make informed decisions under uncertainty

References

1. Thompson, M. G., et al. "Estimates of deaths associated with seasonal influenza-United States, 1976-2007." *Morbidity and Mortality Weekly Report* 59.33 (2010): 1057-1062.
2. Reich, Nicholas G., et al. "A Collaborative Multi-Model Ensemble for Real-Time Influenza Season Forecasting in the US." *bioRxiv* (2019): 566604.

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