Forecasting influenza activity using meteorological and Google Flu Trends data

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OBJECTIVE

Develop a data assimilation system (DAS) to track and forecast outbreaks using Open Source Indicators (OSI) of epidemiological activity

- Test case: Forecast flu activity in CA in a spatially resolved manner
- Data: Use Google Flu Trends (GFT) available at 11 CA cities as data from a "partially observed epidemic"
- Use meteorological data to spatially model flu activity at locations not tracked by GFT
- Validate against public health (PH) data

BACKGROUND

- Disease outbreaks cause changes in our online behavior e.g. web searches on symptoms, cures etc.
- Such searches have proven to be predictive of flu activity [Ginsberg et al, 2009]
- These online OSI are timely and collected by many organizations e.g. GFT
  - In contrast, public health (PH) reporting tends to be delayed by 1-2 weeks and has uneven spatial coverage (reporting is voluntary for most diseases)
- Meteorology can also be a leading indicator of many diseases
  - Rains precede mosquito-borne diseases, low humidity helps flu [Shaman et al, 2010]
  - Further, meteorological data is easily available at high spatiotemporal resolutions (as reanalysis data products)
- Combining OSI and meteorological data could thus be used to forecast flu
  - In [Shaman et al, 2013], the authors developed an ensemble adjustment Kalman filter to assimilate GFT and meteorological data to forecast flu
  - Demonstrated on 100+ US cities tracked by GFT, but no extension to locations outside the cities e.g. suburbs

FUNCTIONAL REQUIREMENTS

- The DAS should be able to provide forecasts of disease activity at locations (called anchors) tracked by GFT
  - For CA, there are 11 cities (anchors) tracked by GFT
- Forecasts should also contain some measure of predictive uncertainty e.g., confidence bounds
- Using nowcasts and forecasts at the anchors, the DAS should (spatially) predict flu activity at locations not directly tracked by GFT
  - High-res meteorological data and the dependence of disease activity on them could be used to construct a spatial model, or parameterization

TECHNICAL APPROACH

Components of a DAS

- A temporal component that sequentially assimilates time-series GFT data and produces forecasts
- A spatial model that predicts flu activity away from the anchors

The temporal component

- Consists of an ensemble Kalman filter (EnKF) driving a SIR model of flu
- Estimates the number of susceptible and infectious people
- Also estimates the mean infectious period and a time-dependent reproductive number
- Assimilation of GFT data produces a "calibrated" SIR model (after sufficient data has been ingested)
- Forecasts using the calibrated model simply means running the ensemble of SIR models forward
  - Produces a mean prediction and (computed) standard deviation σ around it

The spatial model

- Consists of a prior model of flu activity
- Constructed by fitting a linear model to GFT data at each of the anchor locations i, i ε $\mathcal{A}$, with temperature and humidity as predictors

$$GFT^{(i)}(t) = \sum_{k=0}^{K} \alpha_k^{(i)} T^{(i)}(t-k) + \sum_{l=0}^{L} \beta_l^{(i)} Q(t-l) + \varepsilon$$

- $(\alpha^{(i)}_k, \beta^{(i)}_l)$ are interpolated from i, i ε $\mathcal{A}$, to other locations using kernel smoothing
- This leads to a "mean model" ***MM(t)*** that can provide a prior prediction based solely on meteorology, i.e. without GFT data

$$MM^{(j)}(t) = \sum_{k=0}^{K} \alpha_k^{(j)} T^{(j)}(t-k) + \sum_{l=0}^{L} \beta_l^{(j)} Q(t-l) + \varepsilon$$

- The mean model, i.e. $(\alpha^{(i)}_k, \beta^{(i)}_l)$, is trained on historical data
- For any time outside the training period, one computes a discrepancy with respect to the mean model
  - $\Delta I^{(i)}(t) = I^{(i)}(t) - MM^{(i)}(t)$, i ε $\mathcal{A}$
  - $I^{(i)}(t)$ could be GFT data or a temporal forecast at the anchors
  - The discrepancies are interpolated from the anchors to an arbitrary location *j* via kernel smoothing

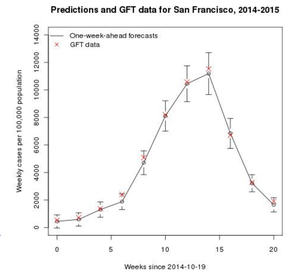
$$I(t;x_j) = \sum_{i,\, i \in \mathcal{A}} K(x_i, x_j)\, I(t, x_i)$$

- This provides a spatial model, or a means or transferring information from the anchors to any other location

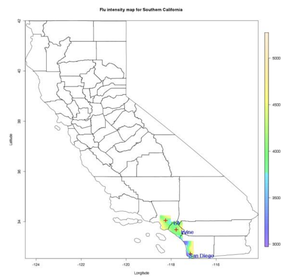
DAS PREDICTIONS

DAS Products

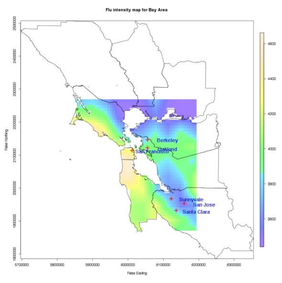
- One-week-ahead flu predictions for a given anchor show predictions and 3σ bounds bracketing the GFT data
  - EnKF is used with 200-member ensembles
  - Data assimilation starts 10 weeks before the start of the flu season
  - Forecasting starts in November
- The spatial model is trained on 2011-2013 GFT and meteorological data
- Together, the DAS produces maps of flu activity
  - Can be nowcasts or forecasts



Forecasts and data for San Francisco, 2014-2015 flu season. Error bars are 3σ bounds

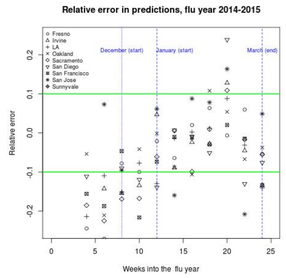


Predictions for Southern California

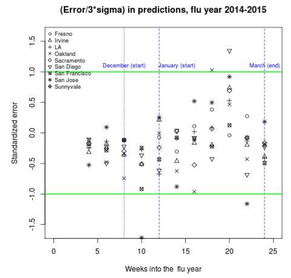


Predictions for San Francisco Bay Area

CHECKING TEMPORAL PREDICTIONS



Relative error in predictions



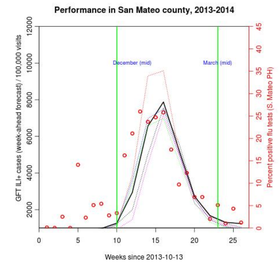
Standardized error

- Temporal predictive skill of the DAS was tested at the anchors
- 1-week-ahead forecasts within 10% of GFT in the January – March period (2014-2015) flu season; 2-week-ahead forecasts are within 20% error
- The 3σ bounds bracket the prediction error during the same period

CHECKING SPATIAL PREDICTIONS

Predicting flu in San Mateo

- Use DAS to provide 1-week ahead forecasts for San Mateo County, CA
- San Mateo is not tracked by GFT
- San Mateo PH department provides a data sheet with percentage of samples testing positive for flu
- Tested with nowcast and forecasts
- Tested on 2013-2014 flu season



CONCLUSIONS

- Open-Source indicators (OSI) of disease outbreaks, such as Google Flu trends, can be used to track and forecast epidemiological activity
- The dependence of epidemiological dynamics on meteorology (temperature and humidity for flu) and the availability of high-resolution meteorological data can be used make a spatial model for epidemiological activity
- A data assimilation system can be set up to assimilate OSI and meteorological data and produce spatiotemporal predictions
- The data streams being used are timely and easily available
- Preliminary tests and comparisons against public health data show that the DAS can be sufficiently accurate to be useful in practice

Acknowledgements

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References

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