EPIDEMIC FORECASTING

Review of the state of the art

Dexter Barrows

April 9 2015

Department of Mathematics and Statistics
McMaster University

Introduction

Techniques

- Phenomenological
- Mechanistic / semimechanistic

Data assimilation

Measuring prediction accuracy

INTRODUCTION

Basics

- Prediction of future values in a time series
- Based on mechanistic understanding, data, mix

Outbreak type

- New disease
  - Scarcity of information is key concern
  - Forecasting extremely difficult
- Established disease
  - Long time series, likely better biological understanding
  - Short-term forecasting is easiest (information plentiful)
  - Long-term forecasting possible, integration of weather/socio-economic factors important

TECHNIQUES

TECHNIQUE TYPES

3 main families

- Phenomenological - pure inference from data
- Mechanistic - capture “drivers” of disease spread
- Semi-mechanistic - integration of data into model

- AutoRegressive Integrated Moving Average
- Purely phenomenological
- Assumes linear process, Gaussian distributions
- 3-parameter process $ARIMA(p, d, q)$, indicating order of
  - p - Autoregressive
    $\rightarrow$ Linear combination of past terms
  - d - Integrated
    $\rightarrow$ Used to remove the trend - makes the series stationary
  - q - Moving average
    $\rightarrow$ Dependence on past error
- Orders are determined using
  - *ACF* - works on consecutive elements in series (correlation)
  - *PACF* - works on additional predictor variables (conditional correlation)

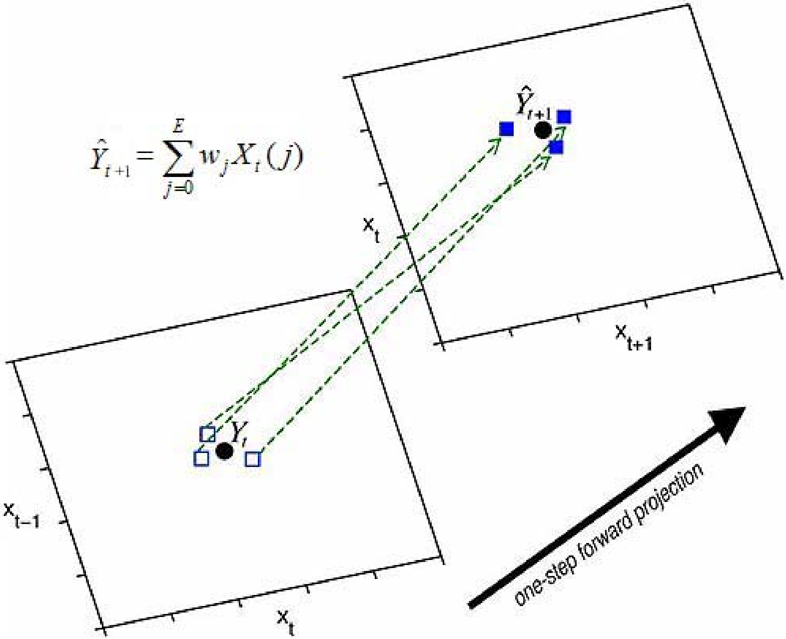
Ref. [9]

SARIMA

- Adaptation of ARIMA used to capture seasonal effects
- Usually expressed as $SARIMA(p, d, q) \times (P, D, Q)_s$
    - P, D, Q are *seasonal* orders
- Orders are determined using
    - *ACF* and *PACF* as before
    - Also Periodic *ACF* (every k elements)

- Construct a “library” of consecutive time lag vectors $\{x_i\}$ of some length E and corresponding forward trajectories $\{y_i\}$
- Use similar past system states with **known** outcomes to project to **unknown** future state
  $\rightarrow$ A weighted linear combination of closest vectors
- Weightings are exponential, function of distance

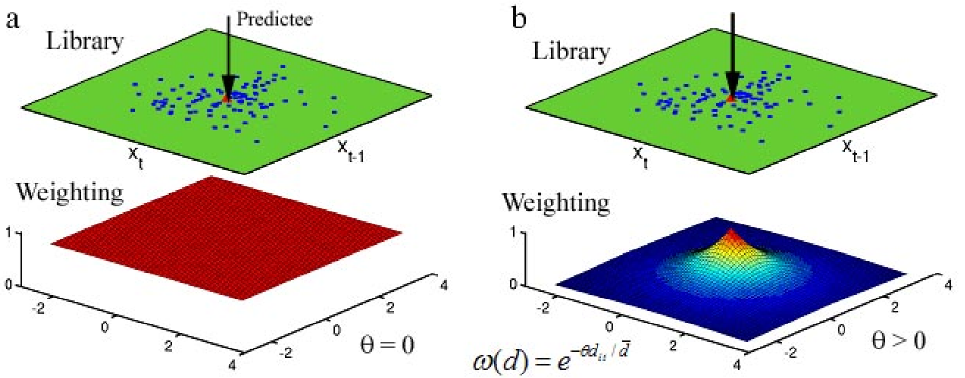
Ref. [2]



http://simplex.ucsd.edu/

- Sequentially locally weighted global linear maps (S-map)
- Designed to handle linear, locally nonlinear time series
- Similar to Simplex projection
  $\rightarrow$ But **all** vectors are used for projection
- Weightings are again exponential

Ref. [2][11]

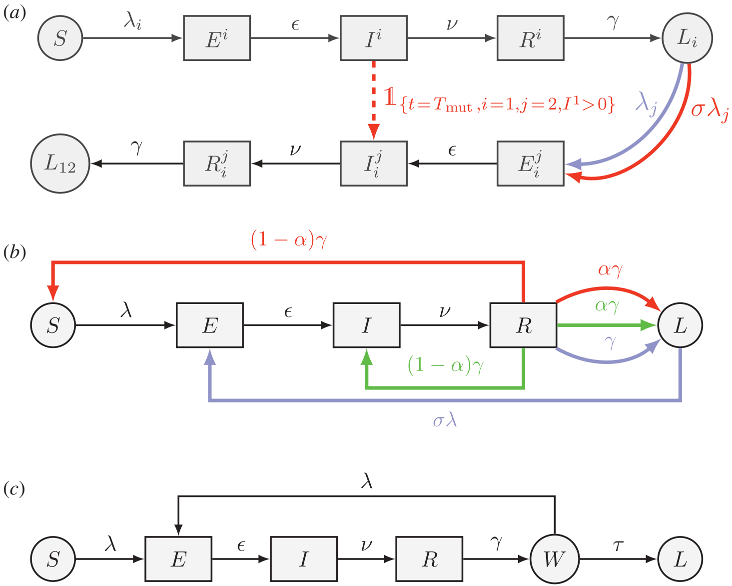


http://simplex.ucsd.edu/

- Extensively used model in epidemiology
- Division into classes: **S**usceptible-**I**nfected-**R**emoved
- Transition between states

$$\frac{dS}{dt} = -\frac{\beta IS}{N}$$
$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma$$
$$\frac{dR}{dt} = \gamma I$$

- Many extensions exist
  - Additional classes
  - Additional mechanistic terms

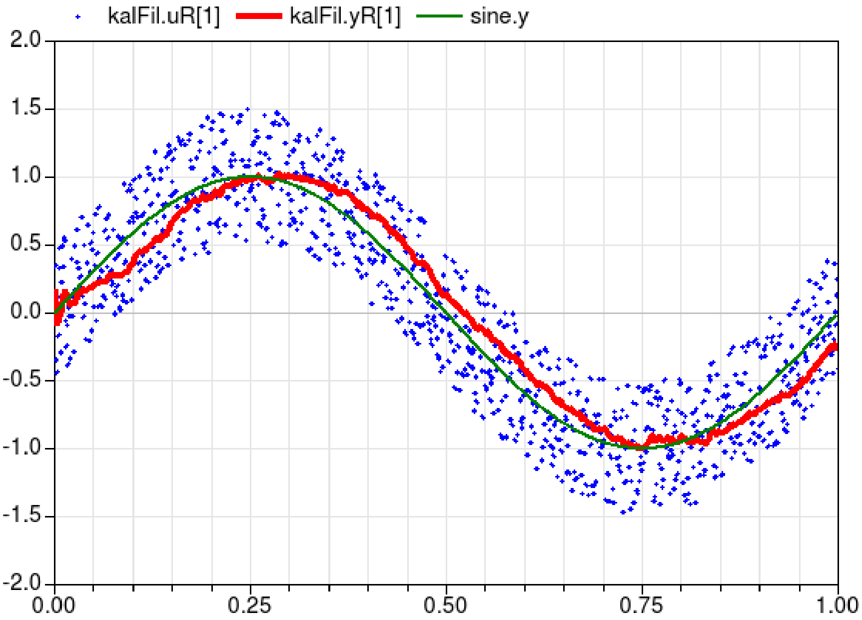


Camacho et al, 2011

Ref. [3]

- SIR-based models *may* require many parameters to be estimated
    - Not a problem if statistical caution is exercised
- Over-fitting a particular problem - can reduce forecasting ability
- More model complexity = longer time series required
- Iterated filtering methods can estimate parameters in addition to producing forecasts

- Designed to operate on linear models, assumptions:
    - Underlying dynamics are linear
    - Error distributions are normal (or close to it)
- Uses knowledge of underlying dynamics (ex. SIR model)
- Operation in cyclical phases
    - Prediction $\rightarrow$ projection forward
    - Update $\rightarrow$ observed data used to refine estimation mechanism



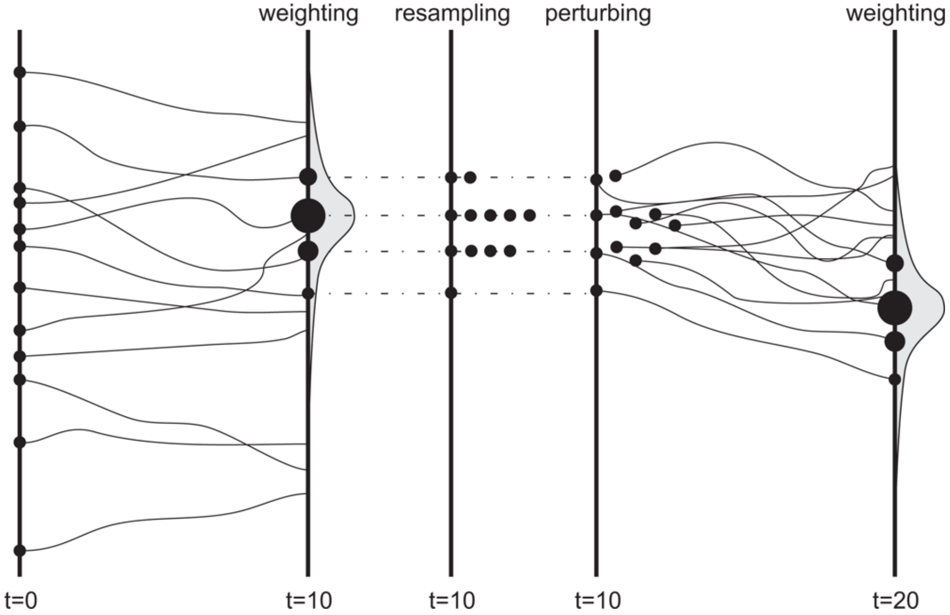
http://simulationresearch.lbl.gov/modelica/releases/latest/help/Buildings_Utilities_IO_Python27_Examples.html

KALMAN FILTER EXTENSIONS

- Extended Kalman filter (*EKF*)
  - Linearises about the estimate of current mean and covariance
- Ensemble Kalman filter (*EnKF*)
  - Uses a cohort of ensemble members, their sample mean and covariance
  - Still assumes linear process / Gaussian distributions
  - Useful for large number of parameters
- Ensemble Adjustment Kalman filter (*EAKF*)
  - Combination of *EKF* and *EnKF*
    - Linearises as in *EKF*
    - Ensemble members as in *EnKF*

Ref. [10]

- Uses a set of particles, similar to *EnKF* cohort
- Makes no assumption about the distributions involved in the system
- Particle importance using weights
- Problem: Particle degeneracy
    - When one particle accumulates most of the weight
    - Avoided via resampling at each iteration



http://www.mdpi.com/sensors/sensors-12-16291/article_deploy/html/images/sensors-12-16291f2-1024.png

- Maximum likelihood via iterated filtering (MIF or IF1)
    - Uses multiple rounds of particle filtering
    - Stochastic perturbation of parameters
    - Each round pushes the parameter estimates toward ML
- Particle Markov chain Monte Carlo (pMCMC)
    - Uses an MCMC method constrain model parameters
    - Particle filter between each MCMC iteration
- IF2 (MIF2)
    - Evolution of MIF (IF1)
    - Uses stochastic perturbation as before, also data cloning
    - Looks to consistently outperform IF1 and pMCMC

Ref. [5][13]

DATA ASSIMILATION

Primary Sources

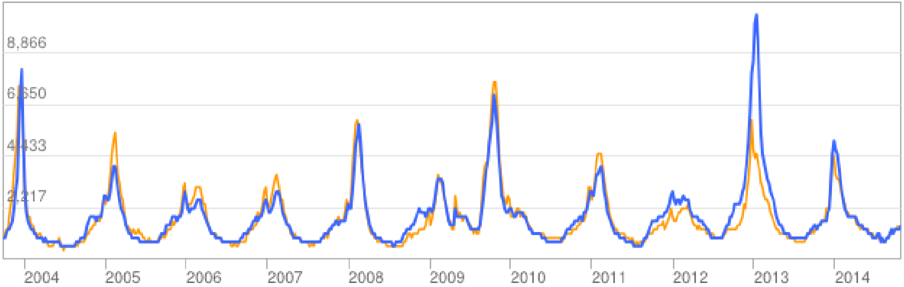
- Google Flu Trends (GFT)
  - Uses search trend data to infer incidence rates
  - Almost instantaneous, but less accurate
  - Currently up to 29 countries
- Governments ex. Centres for Disease Control (CDC)
  - Regional data (10 regions across the US)
  - Broken down further by age
  - More accurate than GFT, but lag of 1-2 weeks
- WHO

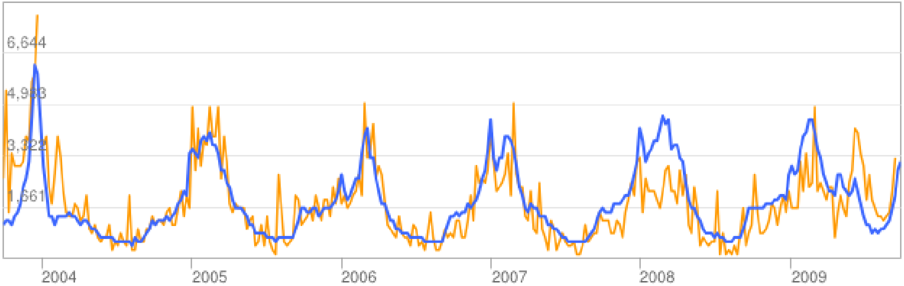
Social Media

- Twitter: Influenza, Korea, 2012
- Social media and informal news: Haiti, Cholera, 2010

Ref. [1][6]

GFT VS CDC FLUNET





https://www.google.org/flutrends/about/how.html

- Nearly all infectious disease affected by seasonality
  - Contact
  - Susceptibility
  - Influx of susceptibles
  - Resevior dynamics / vector dynamics
- Weather data sources
  - National Oceanic and Atmospheric Administration (NOAA)
  - NASA Jet Propulsion Laboratory (JPL)

Ref. [12][13]

- El Ninõ Southern Ocillation
- Sustained anomalous ocean surface temperature in the Pacific
- Unpredictable
- Many effects on local populations
- Relevant to epidemic outbreaks in Southeast Asian locales
    - Cholera in Bangladesh
    - Dengue fever in Singapore

Ref. [4][8]

MEASURING PREDICTION ACCURACY

- What to measure
  - Peak timing / intensity
  - Magnitude
  - Duration
- How to measure
  - Correlation coefficients
  - RMSE
  - Confidence intervals
  - Receiver operating characteristic (ROC) curves

MODEL CRITERIA

- AIC - Akaike Information Criterion
    - Measures relative model quality
    - Rewards goodness-of-fit, penalizes for number of parameters
- BIC - Bayesian Information Criterion
    - Similar to AIC
    - Tends to penalize many parameters more than AIC
- DIC - Deviance Information Criterion
    - Particularly useful when comparing MCMC-based models
- WAIC - Watanabe-Akaike (widely applicable) Information Criterion
    - More “tuned” to prediction

[1] S. Cook, C. Conrad, A. L. Fowlkes, and M. H. Mohebbi.
Assessing Google Flu trends performance in the United States during the 2009 influenza virus A (H1N1) pandemic.
PLoS ONE, 6(8):1–8, 2011.

[2] S. M. Glaser, H. Ye, and G. Sugihara.
A nonlinear, low data requirement model for producing spatially explicit fishery forecasts.
Fisheries Oceanography, 23:45–53, 2014.

[3] A. L. Graham, A. Camacho, F. Carrat, O. Ratmann, B. Cazelles, and L. E.-e. Mathe.
Explaining rapid reinfections in multiple- wave influenza outbreaks : Tristan da Cunha 1971 epidemic as a case study.
Proc. R. Soc. B, 2016.

[4] Y. Hii, J. Rocklöv, S. Wall, and L. Ng.
Optimal lead time for dengue forecast.
PLoS neglected tropical ..., 6(10), 2012.

[5] E. L. Ionides, D. Nguyen, Y. Atchadé, S. Stoev, and A. a. King.
Inference for dynamic and latent variable models via iterated, perturbed Bayes maps.
Proceedings of the National Academy of Sciences, 112(3):719–724, 2015.

[6] E.-K. Kim, J. H. Seok, J. S. Oh, H. W. Lee, and K. H. Kim.
Use of hangeul twitter to track and predict human influenza infection.
PloS one, 8(7):e69305, Jan. 2013.

[7] E. O. Nsoesie, J. S. Brownstein, N. Ramakrishnan, and M. V. Marathe.
A systematic review of studies on forecasting the dynamics of influenza outbreaks.
Influenza and other respiratory viruses, 8(3):309–16, May 2014.

[8] R. C. Reiner, A. a. King, M. Emch, M. Yunus, a. S. G. Faruque, and M. Pascual.
Highly localized sensitivity to climate forcing drives endemic cholera in a megacity.
Proceedings of the National Academy of Sciences of the United States of America, 109(6):2033–6, Feb. 2012.

[9] R. Reyburn, D. R. Kim, M. Emch, A. Khatib, L. von Seidlein, and M. Ali.
Climate variability and the outbreaks of cholera in Zanzibar, East Africa: a time series analysis.
The American journal of tropical medicine and hygiene, 84(6):862–9, June 2011.

[10] J. Shaman, W. Yang, S. Kandula, K. S. Inference, and S. Leone.
Inference and Forecast of the Current West African Ebola Outbreak in Guinea , Sierra Leone and Liberia.
pages 1–17, 2014.

[11] G. Sugihara.
Nonlinear Forecasting for the Classification of Natural Time Series.
Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 348:477–495, 1994.

[12] J. D. Tamerius, J. Shaman, W. J. Alonso, K. Bloom-Feshbach, C. K. Uejio, A. Comrie, and C. Viboud.
Environmental Predictors of Seasonal Influenza Epidemics across Temperate and Tropical Climates.
PLoS Pathogens, 9(3), 2013.

[13] W. Yang, A. Karspeck, and J. Shaman.
Comparison of filtering methods for the modeling and retrospective forecasting of influenza epidemics.
PLoS computational biology, 10(4):e1003583, Apr. 2014.

Thanks for coming!

Questions?