EPIDEMIC FORECASTING

Review of the state of the art

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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

3 main families

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

- **A**uto**R**egressive **I**ntegrated **M**oving **A**verage
- 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)

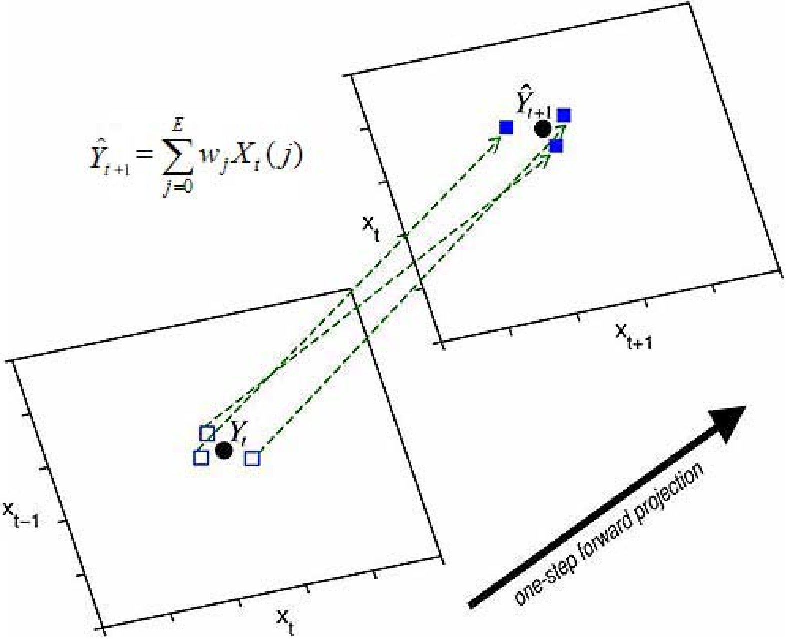
[9]

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

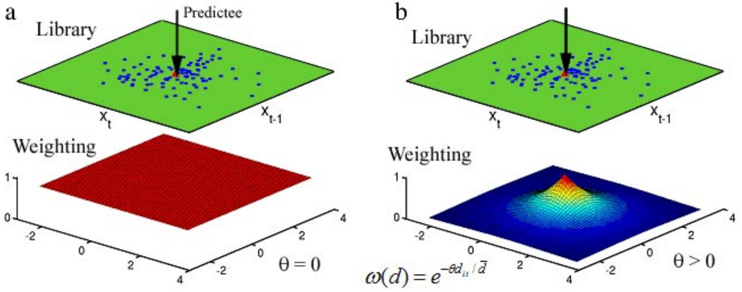
[2]



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

[2][11]

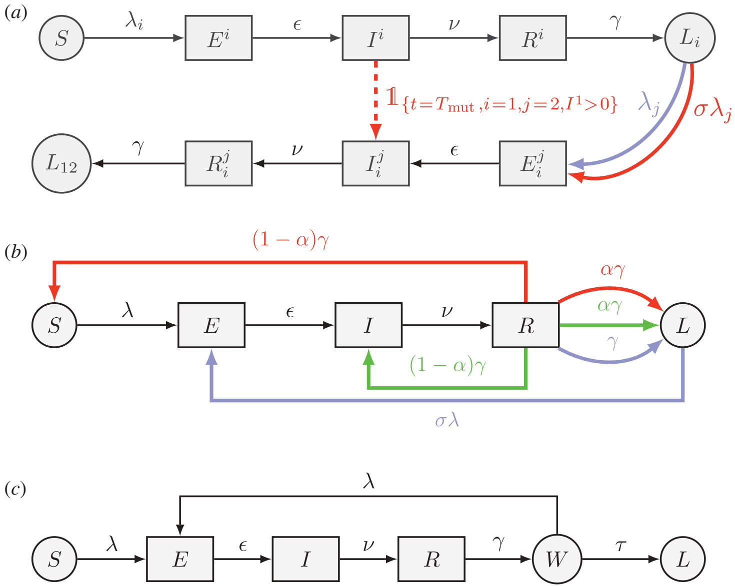


http://simplex.ucsd.edu/

- Extensively used model in epidemiology
- Division into classes: Susceptible-Infected-Removed
- Transition between states

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

- Many extensions exist
  - Additional classes
  - Additional mechanistic terms



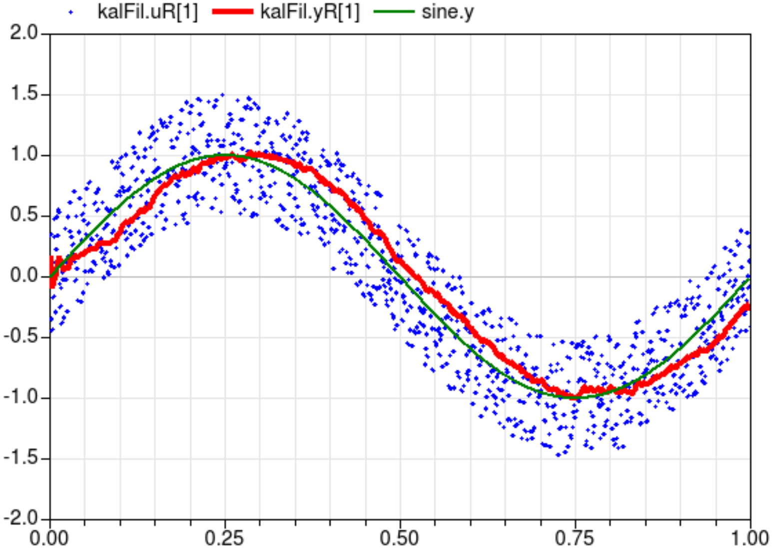
Camacho et al, 2011

[3]

PARAMETER FITTING

- 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

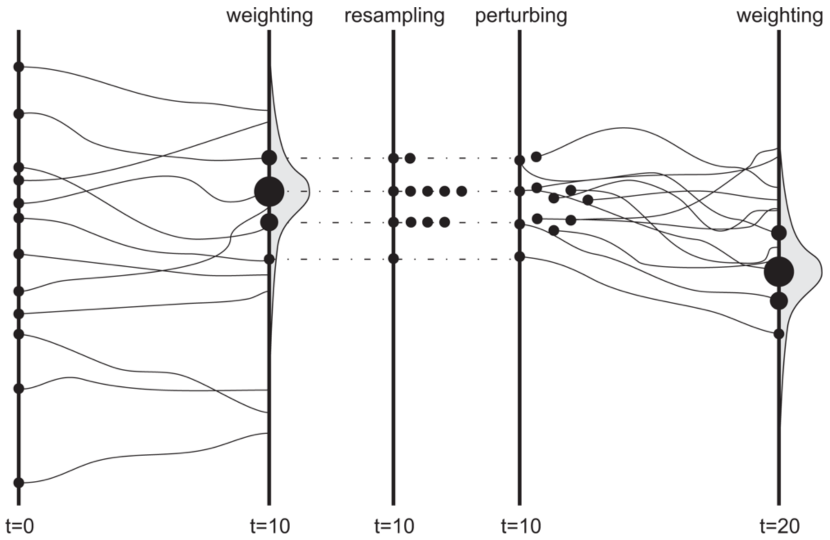


http://simulationresearch.lbl.gov/modelica/releases/latest/help/Buildings_Utilities_IO_Python27_Examples.html

- 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*

[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

[5][13]

DATA ASSIMILATION

Primary Sources

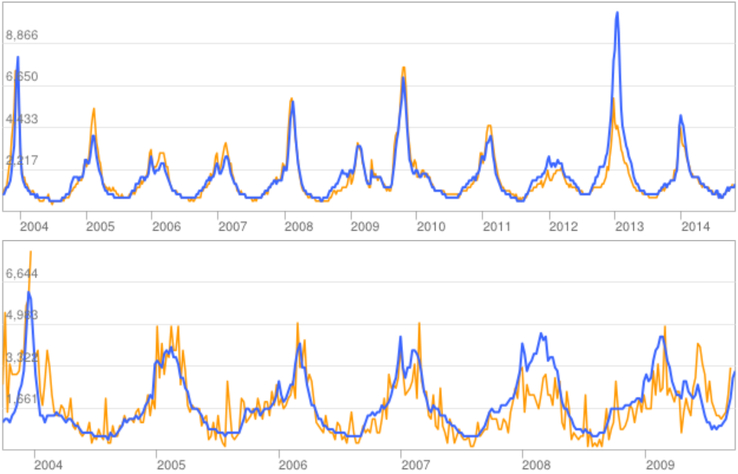
- Google Flu Trends (GFT)
  - Uses search trend data to infer incidence rates
  - Almost instantaneous, but less accurate
  - Currently up to 29 countries
- Governments ex. Centres for Disease Control (CDC)
  - Regional data (10 regions across the US)
  - Broken down further by age
  - More accurate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

Social Media

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

[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)

[12][13]

ENSO

- 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

[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

- 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

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Thanks for coming!

QUESTIONS?