

Characterization of Communicable Disease Epidemics using Bayesian Inference

Cosmin Safta¹, Jaideep Ray¹, Karen Cheng² and David Crary²

¹Sandia National Laboratories, Livermore CA, ²Applied Research Associates, Inc, Arlington, VA

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Ms. Karen Cheng at ARA, is the Principal Investigator. Contact Info: kcheng@ara.com and csafta@sandia.gov





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- Problem Formulation Numerical Approach
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 - Speed-up of the Parameter Inference Surrogate Models
- Conclusions and Acknowledgement



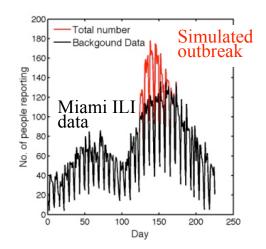
Motivation & Approach

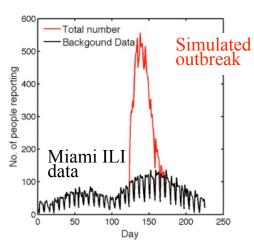
- Disease models are used in planning, resource allocation etc.
 - They contain parameters which have to be supplied
 - Generally biosurveillance data is used to detect, not characterize outbreaks (some exceptions – Held et al, Stats. Modelling, 2005)
- To develop statistical techniques that can characterize an epidemic from biosurveillance data
 - Characterization of the epidemic- estimate number of index cases, (time-dependent) spread rate, etc
 - NOT trying to characterize the pathogen no genetic, immune-system response, etc.
 - Use biosurveillance data and real-time estimation
 - Estimates will be highly uncertain, so need to quantify uncertainty
- Questions
 - How small an epidemic can we detect and characterize?
 - What can we characterize with useful uncertainty bounds?



A Communicable Disease Example

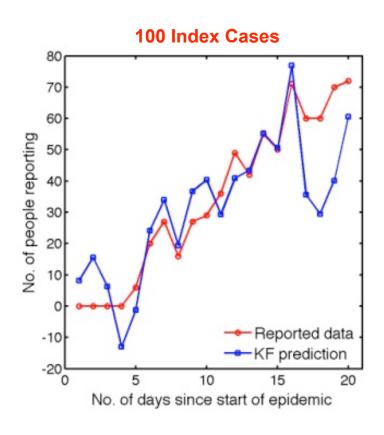
- A simulated plague epidemic
 - Performed with an agent-based model for disease spread; includes visit-delay
 - Disease parameters from Gani & Leach, EID, 2004
 - Insert into ICD-9 stream for ILI from Miami
 - 100/1000 index cases; epidemic dies out in 40 days
- Extract epidemic, per Ray et al, CBD Conf,
 Orlando, 2010
- Aim:
 - Estimate the total size of the epidemic
 - Also, the infection rate and visit delay curves
 - Compare with the "true" figures from the simulation

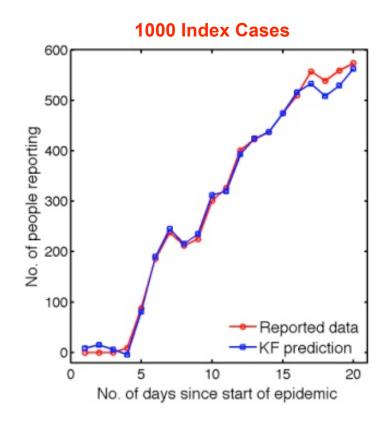






Extraction of the Epidemic

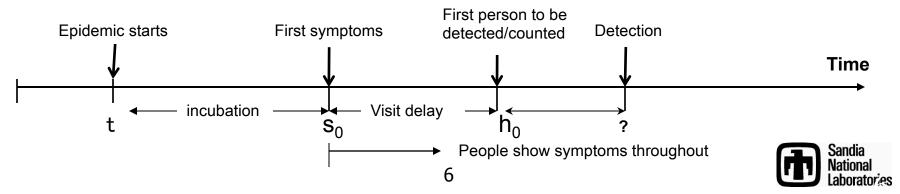






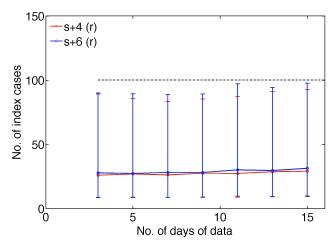
Formulation of the Problem

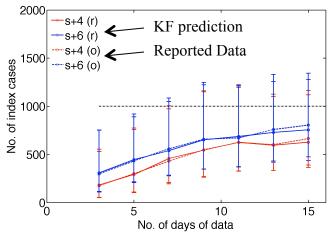
- Data the extracted epidemic: time-series of counts of people seeking care, on a daily basis
- Model A convolution of a time-dependent infection rate (1 free parameter), incubation period (known), and visit delay (1 free parameter)
 - Also includes <u>total size</u> of the epidemic, <u>time of infection</u> of the index cases and <u>fraction of index cases</u> as free parameters (Brookmeyer's 1988)
 - 5 free parameters in all
- Fitting
 - Estimate the PDFs of the 5 parameters using an adaptive Markov Chain Monte Carlo (MCMC) approach
 - Takes about 1-3 hrs depending upon the length of the time-series



Estimation of the No. of Index Cases

- The true values are 100 and 1000, respectively
- The estimate improves with time (and data!) for larger outbreaks
- Estimates performed with data starting from
 - Start of epidemic + 4 (s+4)
 - Start of epidemic + 6 (s+6)
- Easier for large outbreaks



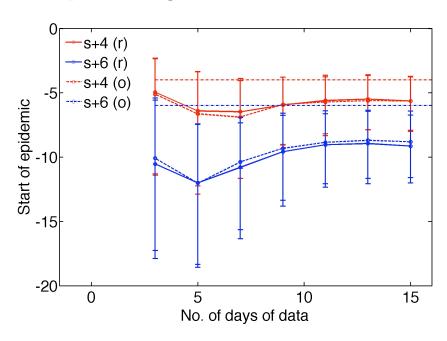


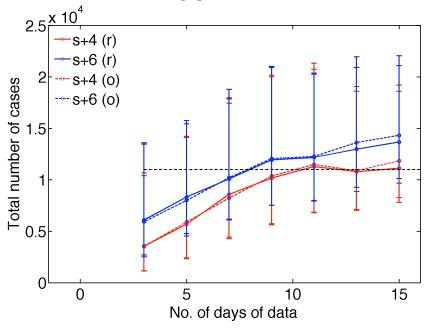


Estimation of the Start of the Epidemic and its Total Size

Epidemic starts 4 and 6 days, respectively, before data collection

Total size true value is approx. 11000

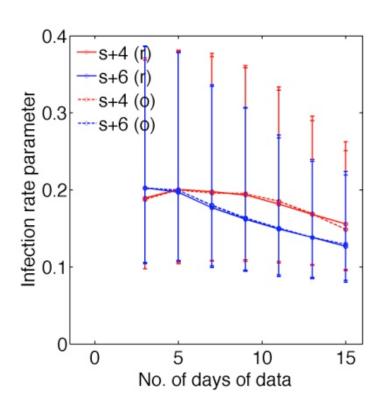


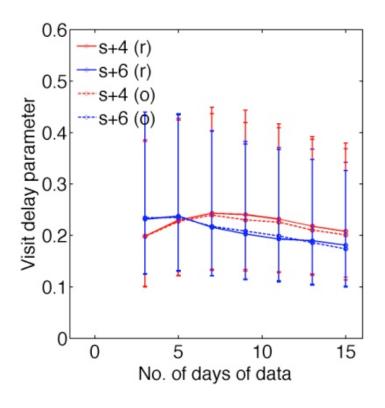




Estimation of the Parameters in InfectionRate and Visit Delay Models

- Both modeled as a *\(\Gamma\)-functions*
 - rate parameters are inferred; shape parameters are set

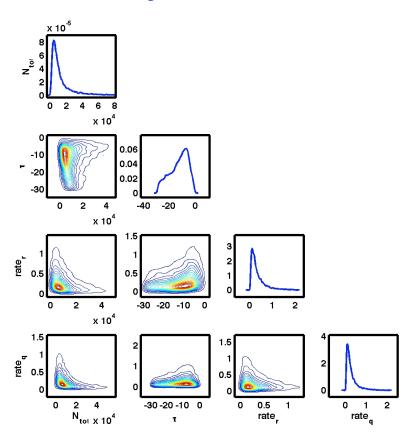




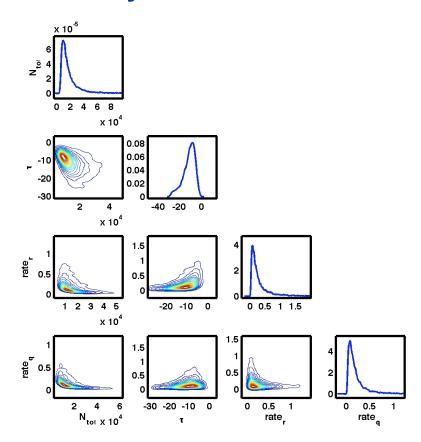


Joint Probability Distributions of the Inferred Parameters

5 Days of Data

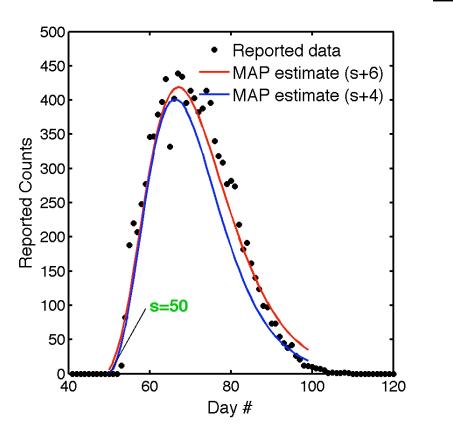


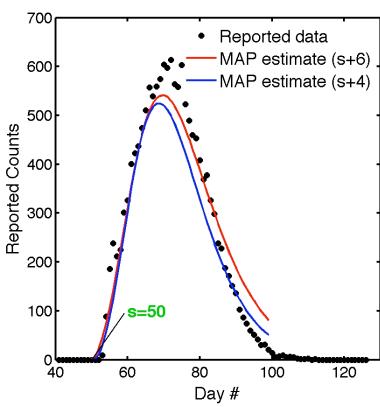
15 Days of Data





Estimation of the Epidemic's Progression





- Best estimate based on maximum a-posteriori (MAP) distribution
- Developed using 15 days of data, starting 4 and 6 days, respectively, after first 1000 people got infected



Speed up the Inference – Surrogate Models

$$\begin{split} & v_{ind} \left(\left(t_{i}, t_{i+1} \right] \right) = N_{tot} (1 - \alpha) \int_{\tau}^{t_{i+1}} f_{inc} (s - \tau) \left[F_{vd} \left(t_{i+1} - s; r_{vd} \right) - F_{vd} \left(t_{i} - s; r_{vd} \right) \right] ds \\ & v_{sec} \left((t_{i}, t_{i+1}) \right) = N_{tot} \alpha \int_{w = \tau}^{t_{i+1}} \int_{u = \tau}^{t_{i+1}} q_{inf} (u - \tau; r_{ir}) f_{inc} (w - u) \left[F_{vd} \left(t_{i+1} - w; r_{vd} \right) - F_{vd} \left(t_{i} - w; r_{vd} \right) \right] du dw \\ & v_{tot} = v_{ind} + v_{sec} \end{split}$$

- Double integral is very costly during the MCMC sampling
- Create a surrogate for the epidemic model and compute it offline
 - Use Polynomial Chaos representations (Ghanem & Spanos, 1991): accurate with respect to the pdf's of interest and fast to evaluate.

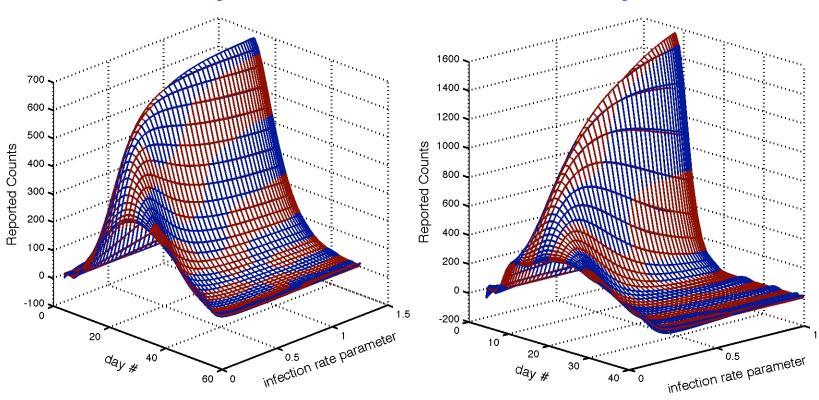
$$v_{tot}(t) = \sum_{k=1}^{P} a_k \Psi_k^{(6)}(N_{tot}, \alpha, \tau, r_{vd}, r_{ir}, t) \rightarrow v_{tot}(t - \tau) = N_{tot} \sum_{k=1}^{P} (b_k + c_k \alpha) \Psi_k^{(3)}(r_{vd}, r_{ir}, t)$$



Surrogate Models – cont'd

Visit delay rate = 0.2

Visit delay rate = 1.0



- •Red mesh → direct model
- Blue mesh → surrogate model





- Early in the development of a techniques to characterize epidemics
 - Working off biosurveillance data
 - Provides information on the particular/ongoing outbreak
 - Second half of a detect-and-characterize algorithm; model selection algorithm is also in place
- Parameter estimation capability ideal for providing the input parameters into an agent-based model
 - Index cases, spread/infection rate, total epidemic size, etc
 - Since it's real-time, can be used to check if medical interventions are effective
- To do
 - Tests with different kinds of background models
 - Tests with outbreaks of different sizes and spread/infection rates
 - Identification of a "proper" set of ICD-9 codes for monitoring biosurveillance data streams





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Ms. K. Cheng at Applied Research Associates, Inc, is the PI

