



 International Clinics on
 Infectious Disease
 Dynamics and Data:
 The ICI3D Program


SACEMA
DST/NRF Centre of Excellence in Epidemiological Modelling and Analysis



AIMS
SOUTH AFRICA

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Likelihood Fitting and dynamic models: Part I (Updated: 5 June 2015)
 Attribution: JRC Pulliam and SE Bellan, Clinic on the Meaningful Modeling of Epidemiological Data
 Source URL: http://mmed2015.ici3d.org/lectures/fittingDynamicModels_PartI.pdf
 For further information please contact faculty@ici3d.org.

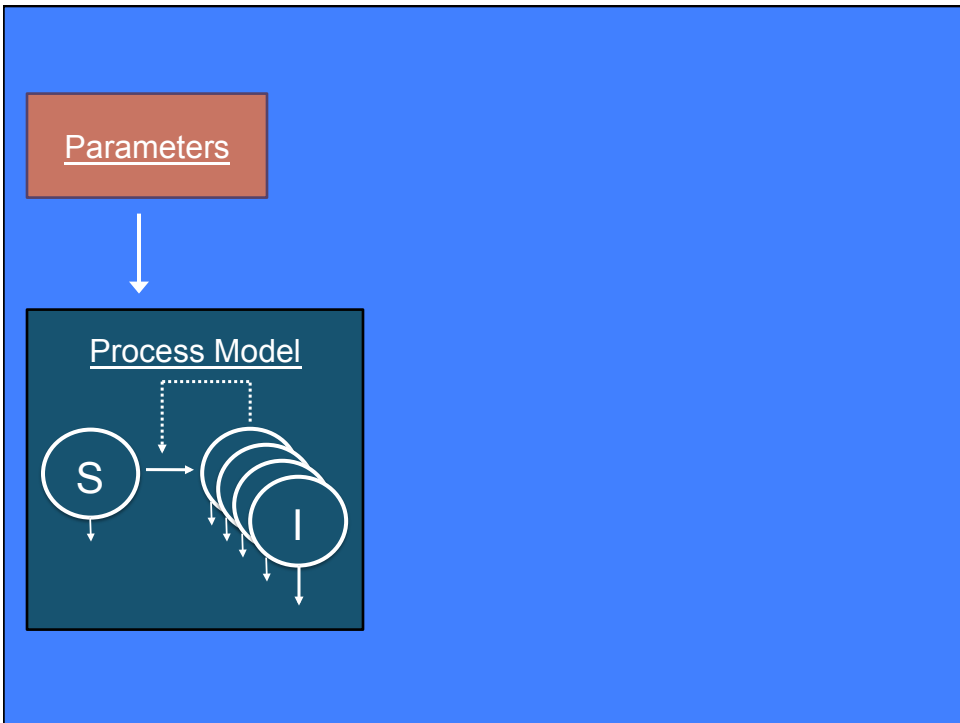
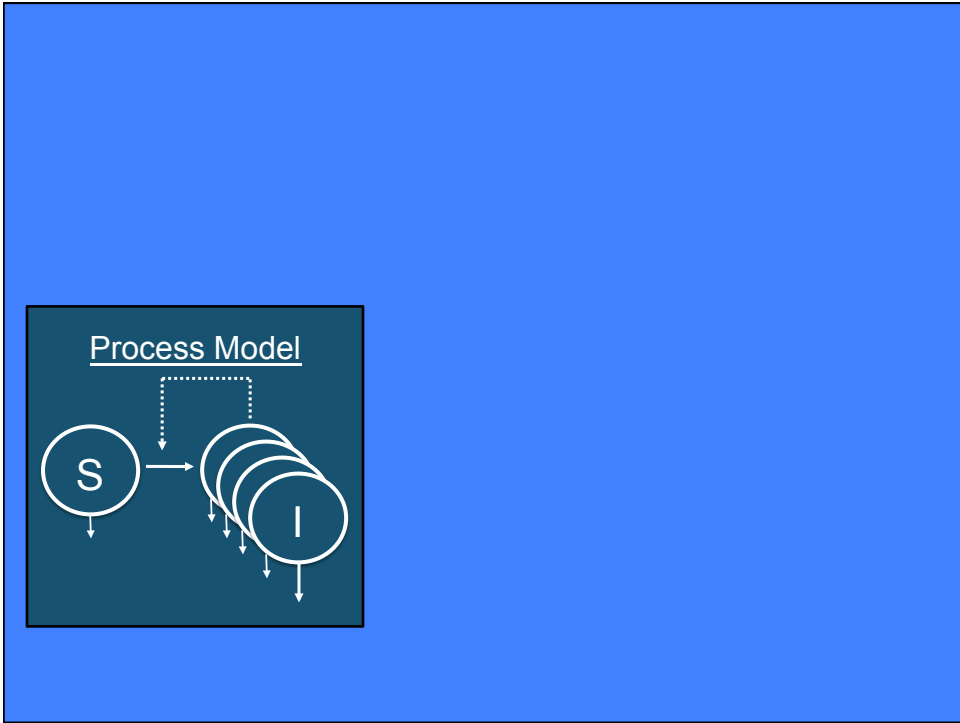


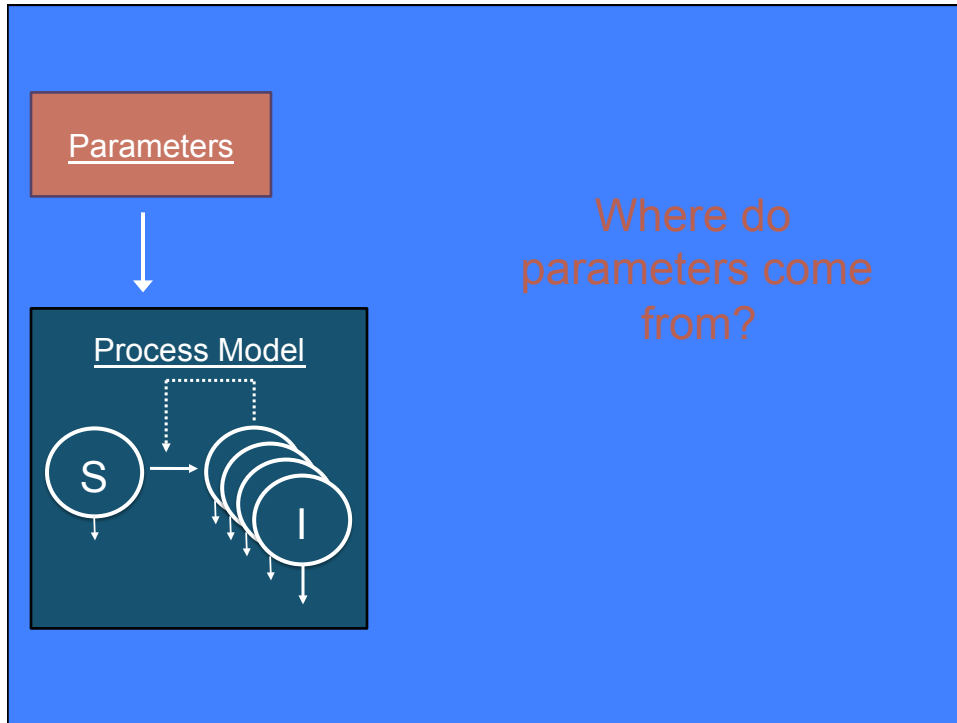
Likelihood fitting and dynamic models: Part 1

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 Department of Biology and
 Emerging Pathogens Institute
 University of Florida

June 5, 2015

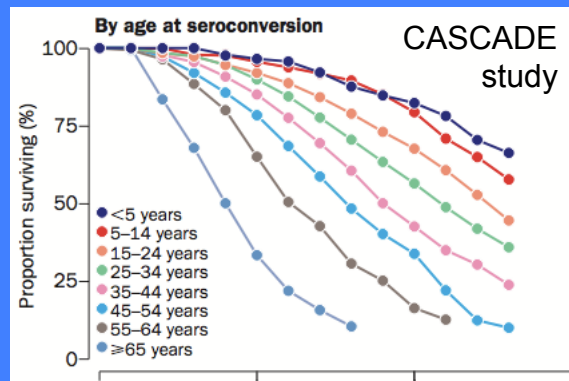
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 ICI3D Program and AIMS - South Africa





A priori parameterization

- Use external data to determine values for the parameters in your model



A priori parameterization

- Use external data to determine values for the parameters in your model
 - eg, time from seroconversion to death

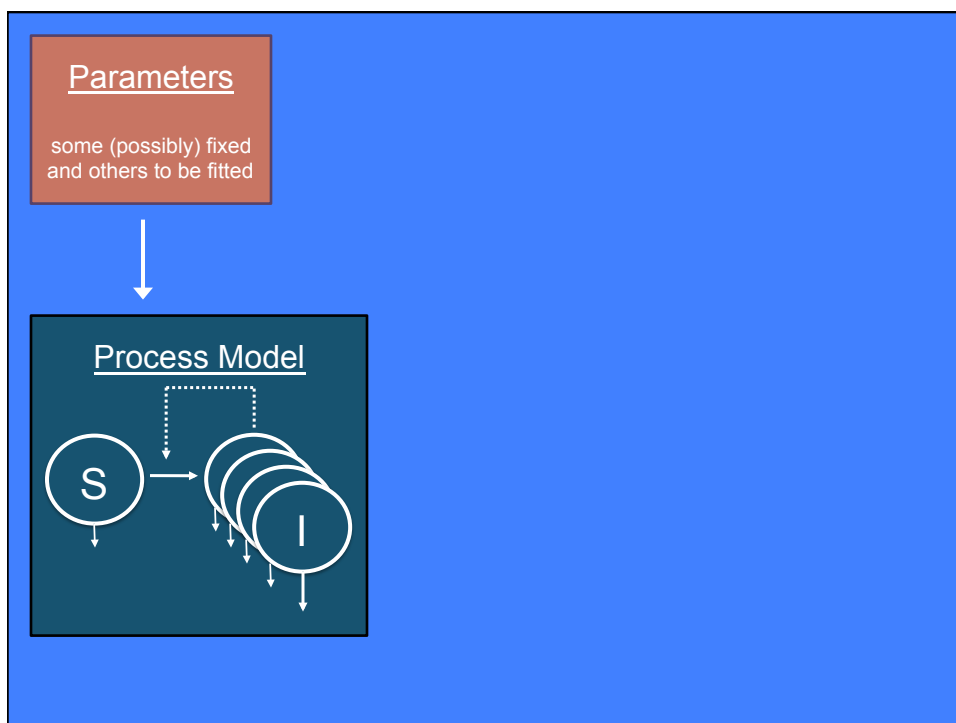
- Plug estimates into models to determine expected dynamics

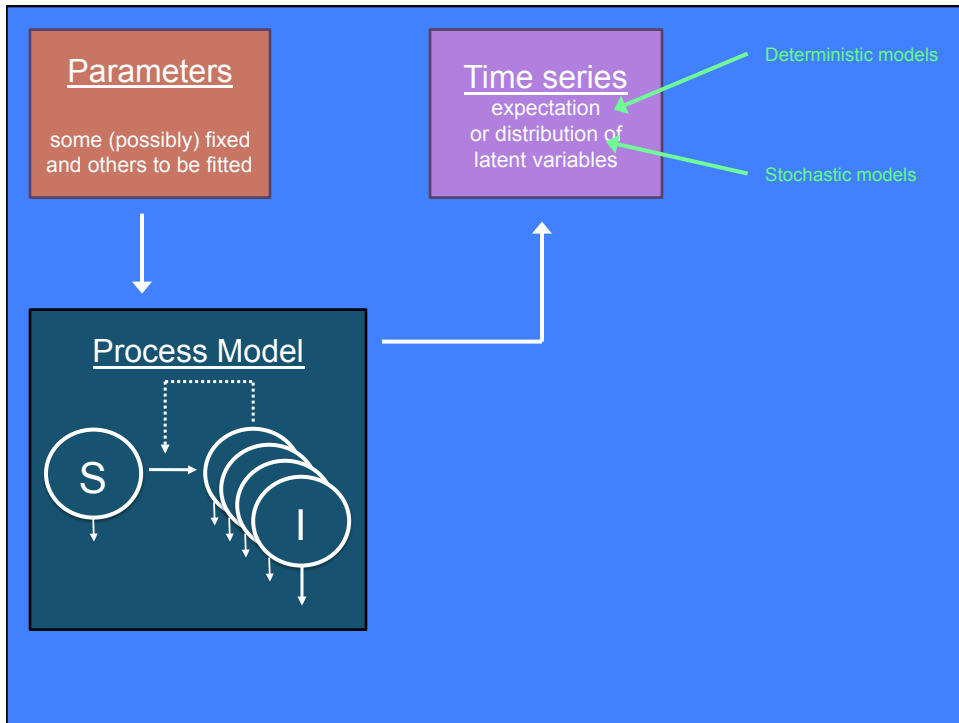
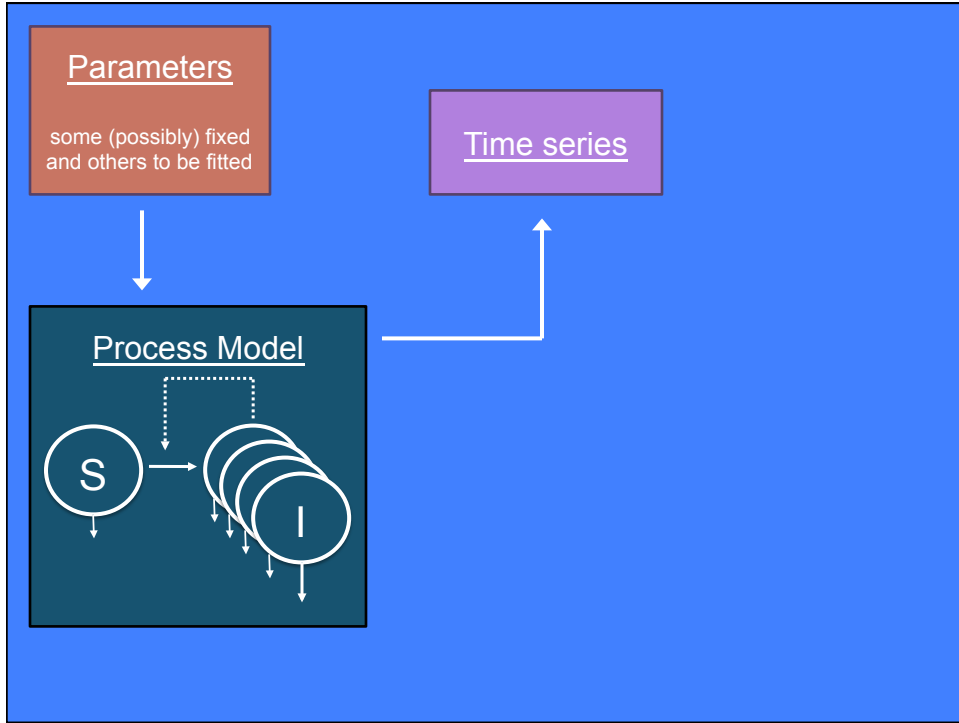
Fitting models to data

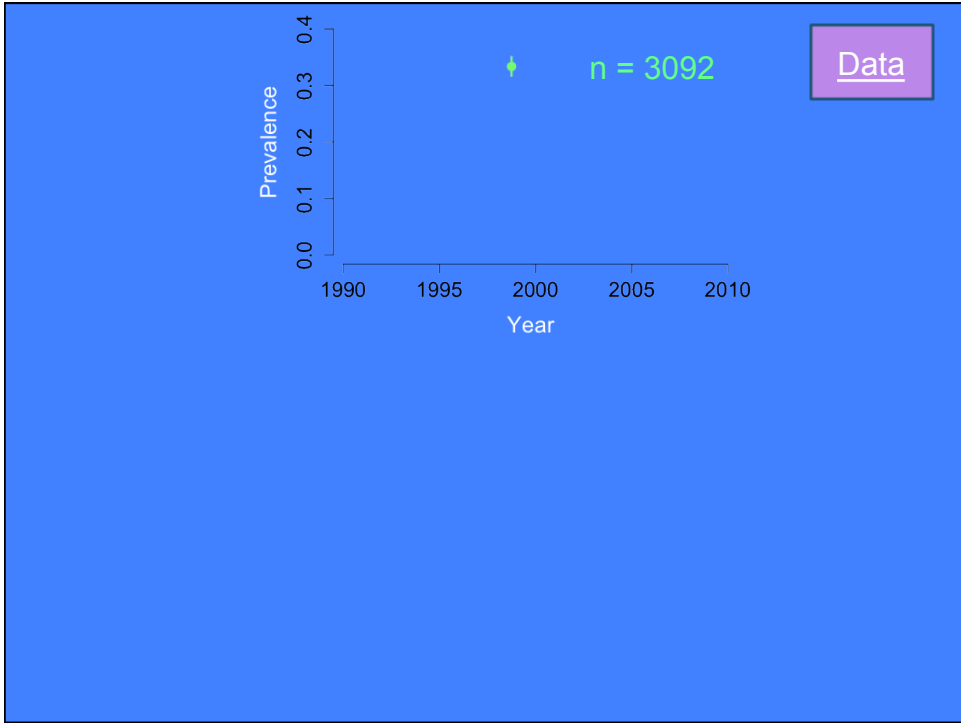
- *A priori* parameterization
 - Use external data to determine values for the parameters in your model
 - Rarely possible for all model parameters

Fitting models to data

- *A priori* parameterization
 - Use external data to determine values for the parameters in your model
 - Rarely possible for all model parameters
- Trajectory matching
- Feature matching







Prevalence

Year

n = 3092

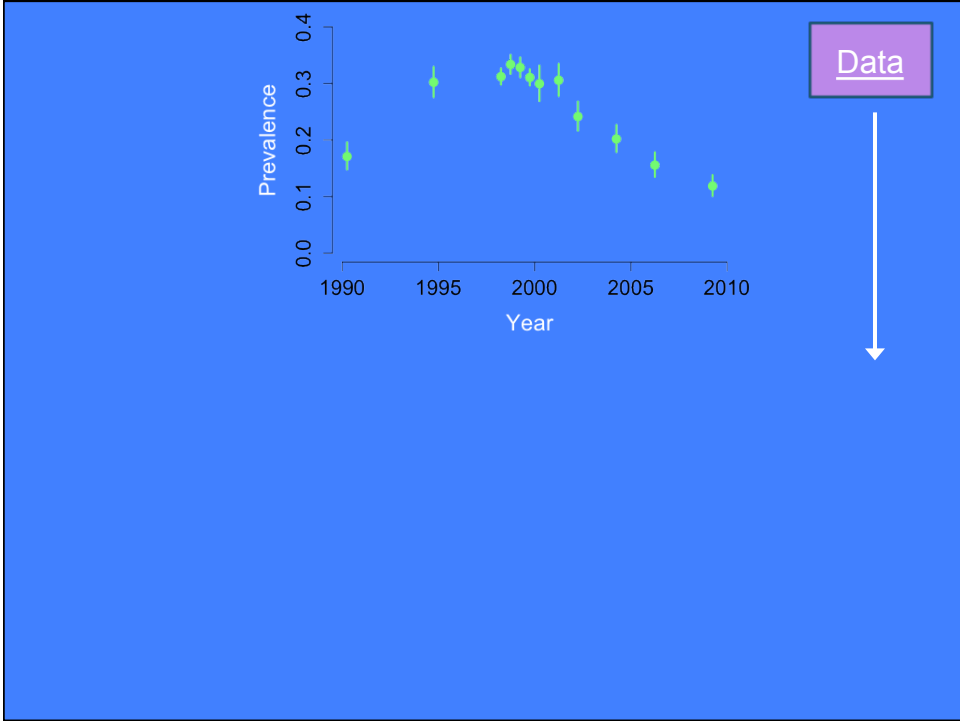
Data

PDF: $f(x | p) = \binom{n}{x} p^x (1 - p)^{n-x}$

Observation model

LIKELIHOOD: $L(p | x) = \binom{n}{x} p^x (1 - p)^{n-x}$

Likelihood of prevalence (given data)



Prevalence

Year

Data

PDF:

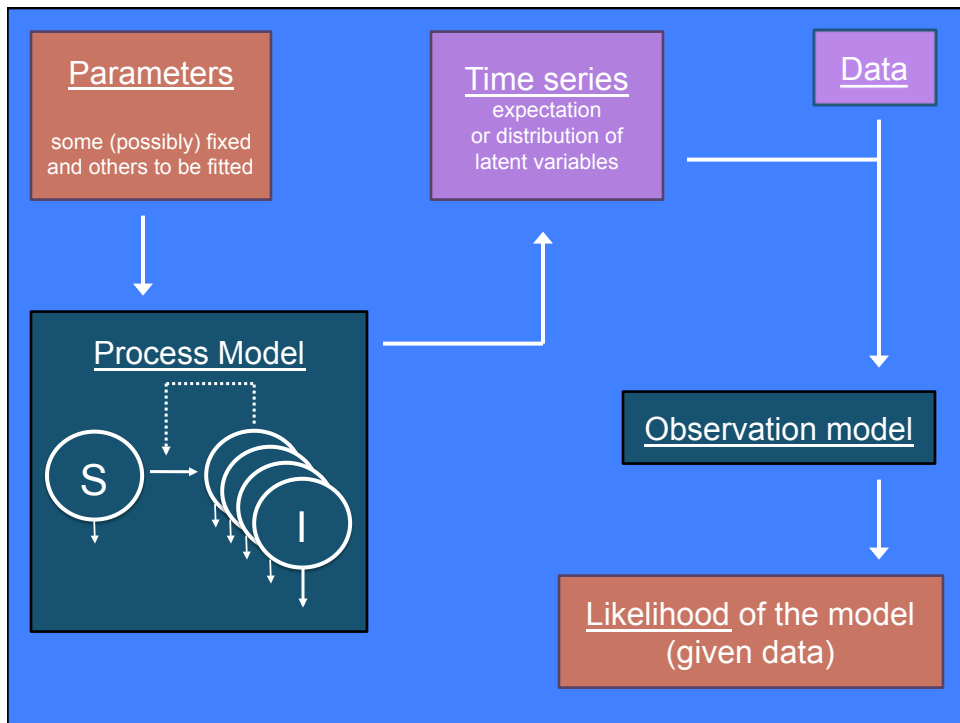
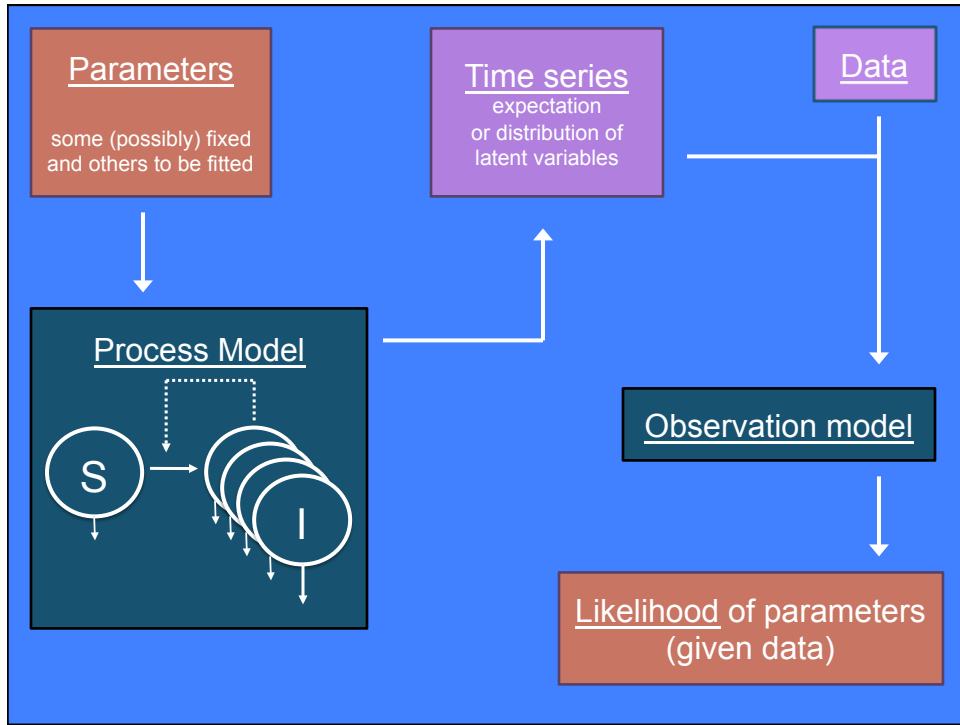
$$f(x_t | p_t) = \prod_t \binom{n_t}{x_t} p_t^{x_t} (1 - p_t)^{n_t - x_t}$$

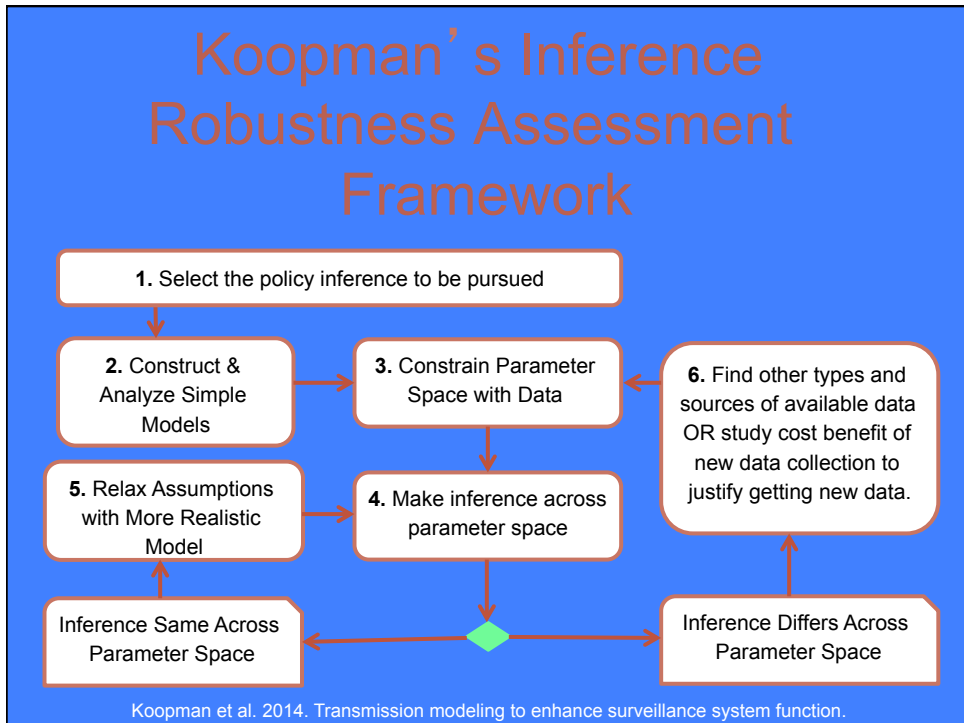
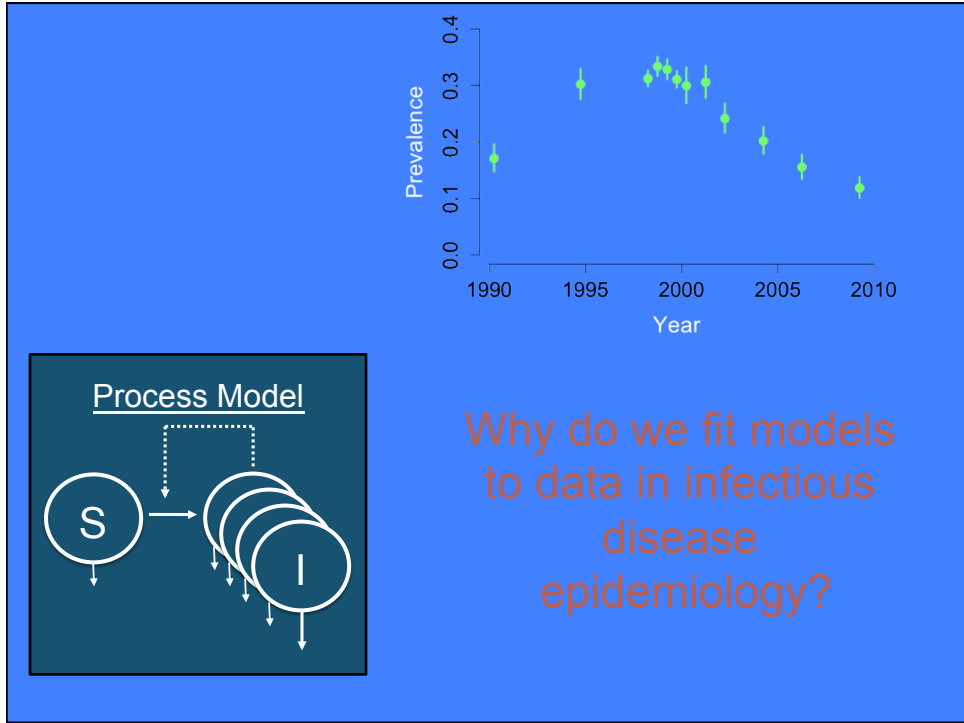
LIKELIHOOD:

$$L(p_t | x_t) = \prod_t \binom{n_t}{x_t} p_t^{x_t} (1 - p_t)^{n_t - x_t}$$

Observation model

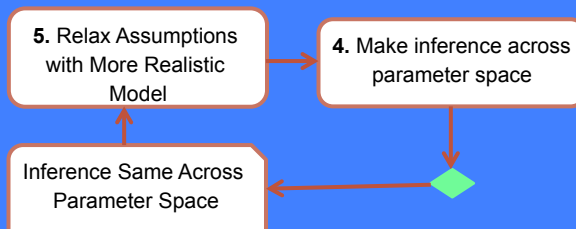
Likelihood of prevalence trajectory (given data)





Koopman's Inference Robustness Assessment Framework

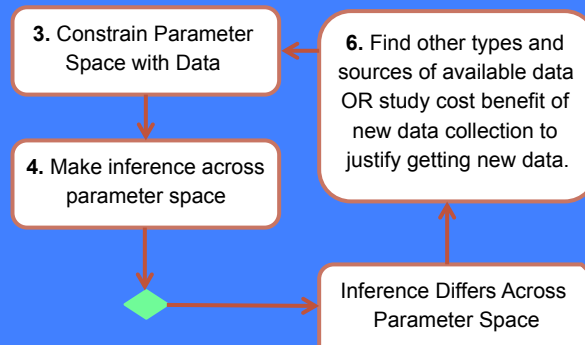
Inference Robustness Assessment Loop



Koopman et al. 2014. Transmission modeling to enhance surveillance system function.

Koopman's Inference Robustness Assessment Framework

Inference Identifiability Assessment Loop



Koopman et al. 2014. Transmission modeling to enhance surveillance system function.

Koopman's Inference Robustness Assessment Framework

- Assess inference robustness to realistic relaxation of simplifying model assumptions
- Pursue complexity that matters by keeping models as simple as possible but not **so** simple that they lead to an incorrect inference

Validate the inference!

not the model or method you're working with

Koopman et al. 2014. Slide courtesy of JS Koopman (with modification).