Likelihood fitting and dynamic models, Part 1:

Dynamic model fitting and inference robustness

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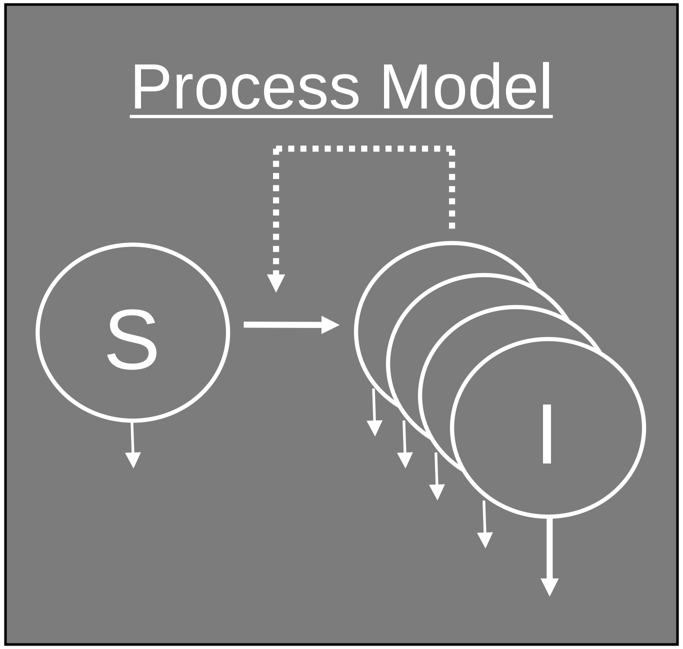
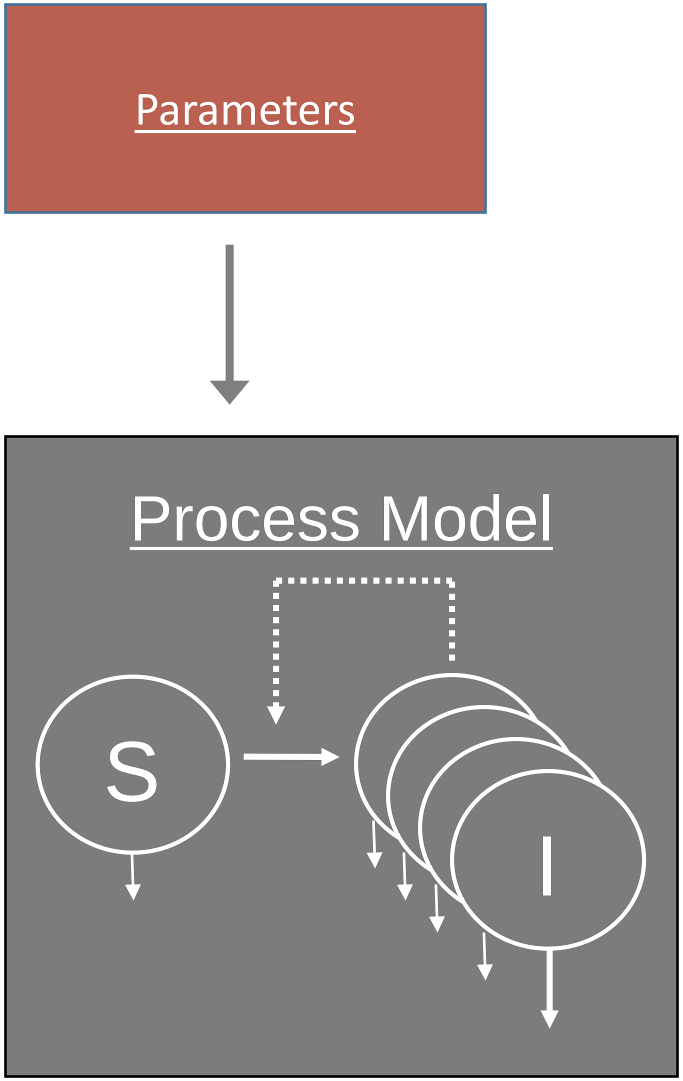
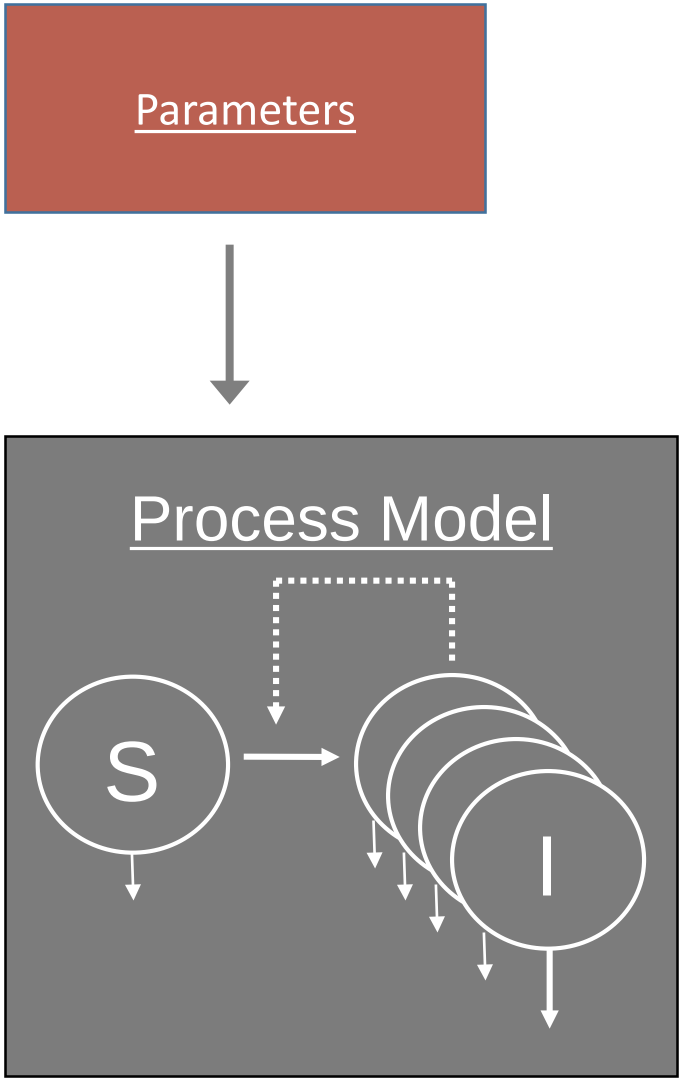
Goals

- Review key points presented throughout the week
- Begin to integrate the **statistics and data** theme with the **dynamic models and model structures** theme


Process Model
S
I

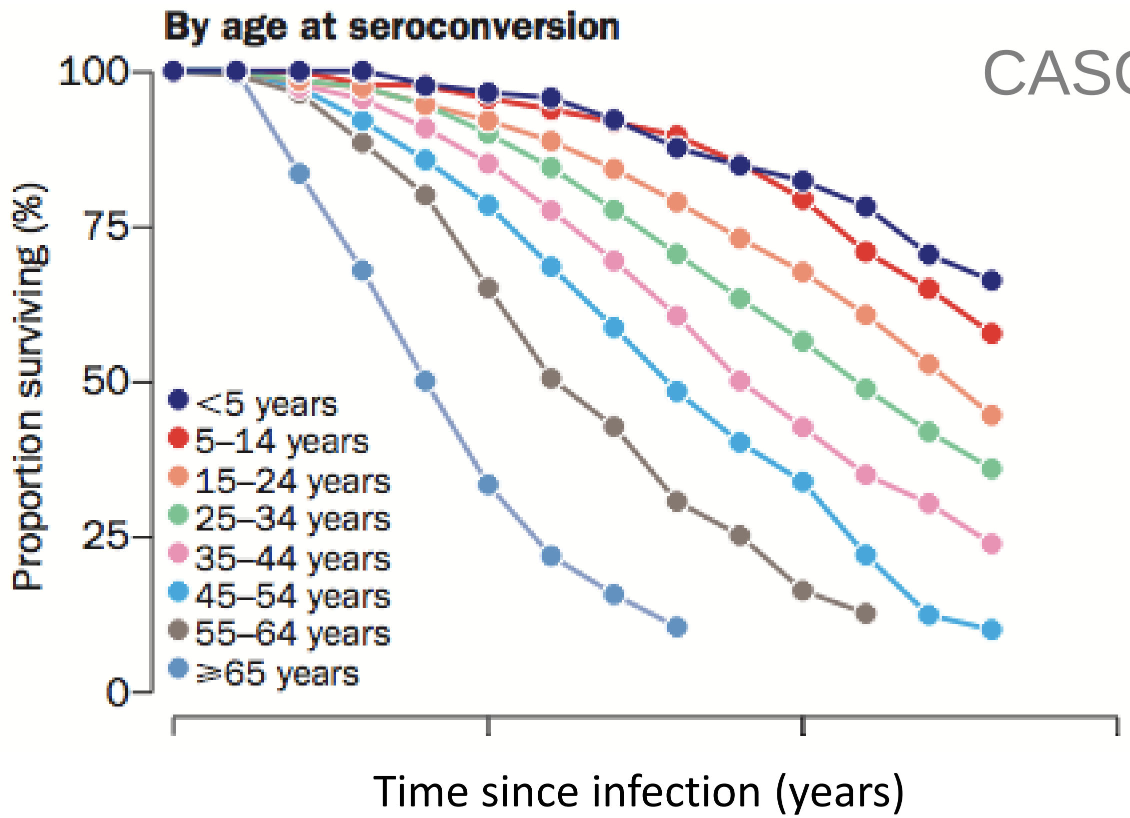

Parameters
Process Model
S
I



Where do parameters come from?

A priori parameterization

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



CASCADE study

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

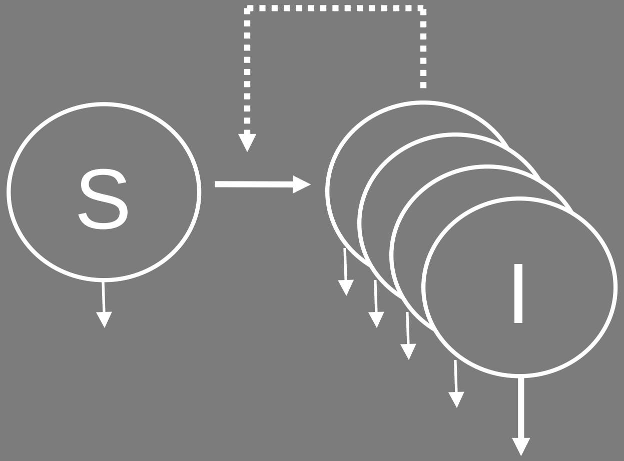
Fitting models to data

- *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

Parameters

some (possibly) fixed
and others to be fitted

Process Model

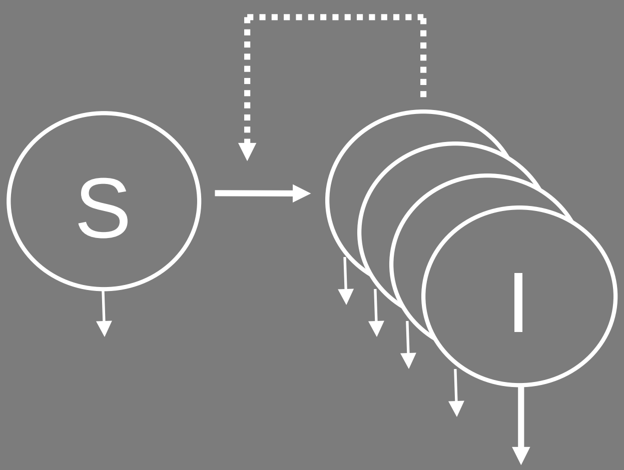


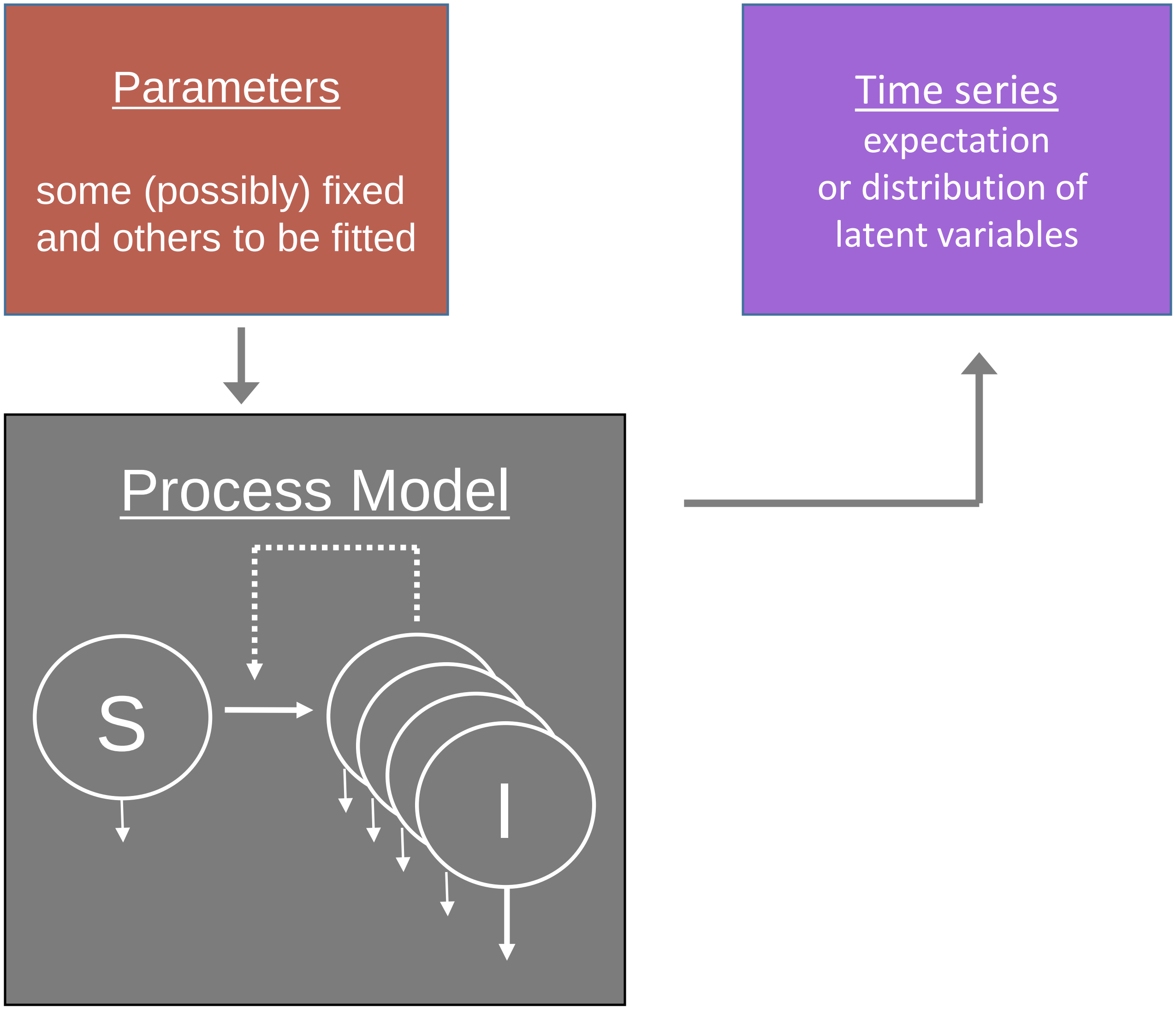
Parameters

some (possibly) fixed
and others to be fitted

Time series

Process Model




Parameters
some (possibly) fixed
and others to be fitted
Time series
expectation
or distribution of
latent variables
Process Model
S
I

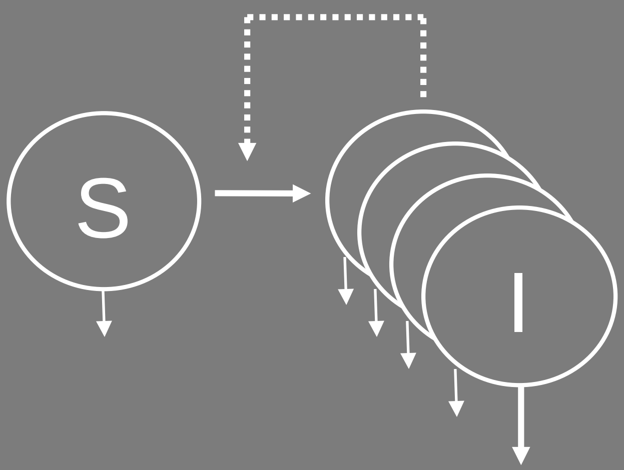
Parameters

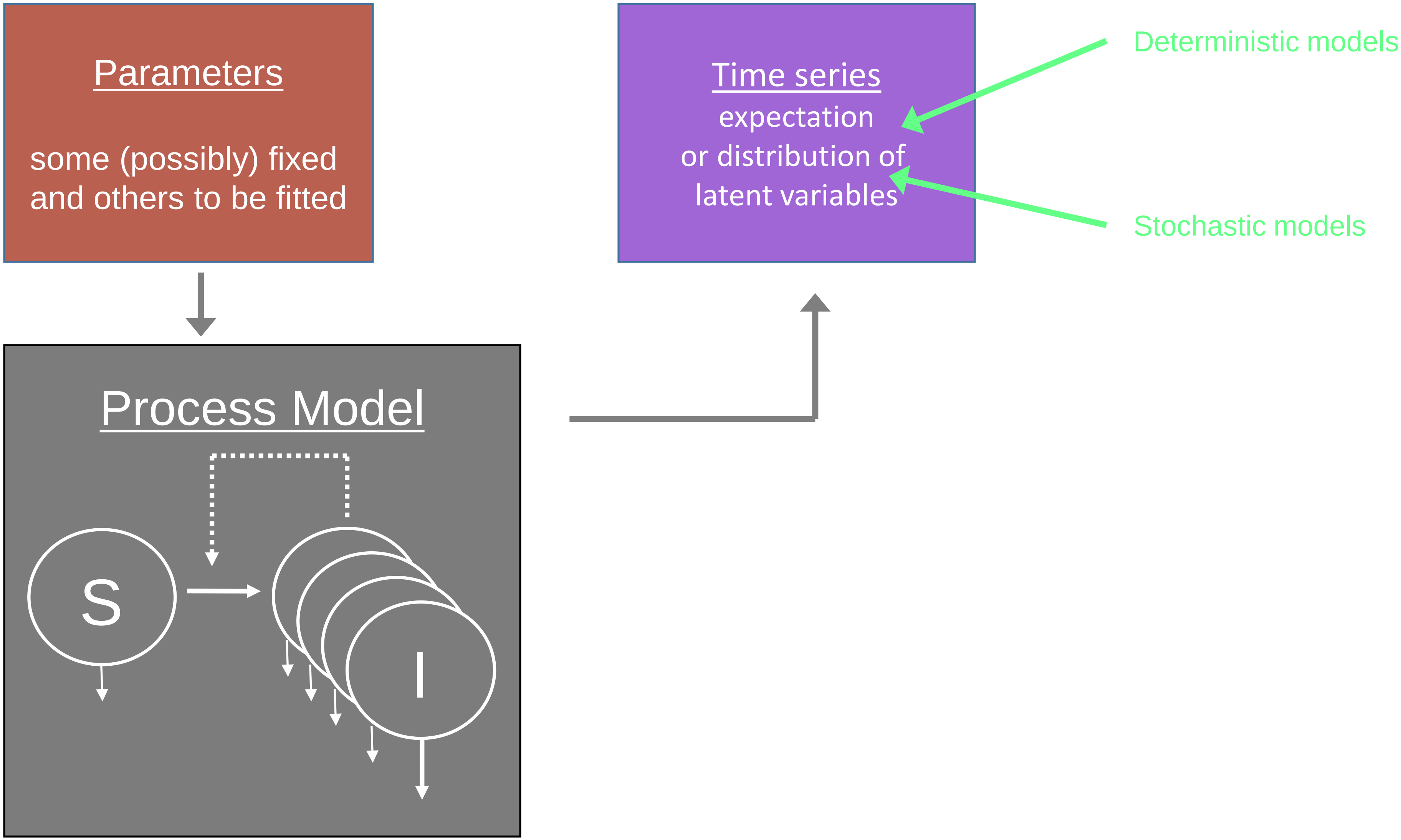
some (possibly) fixed
and others to be fitted

Time series
expectation
or distribution of
latent variables

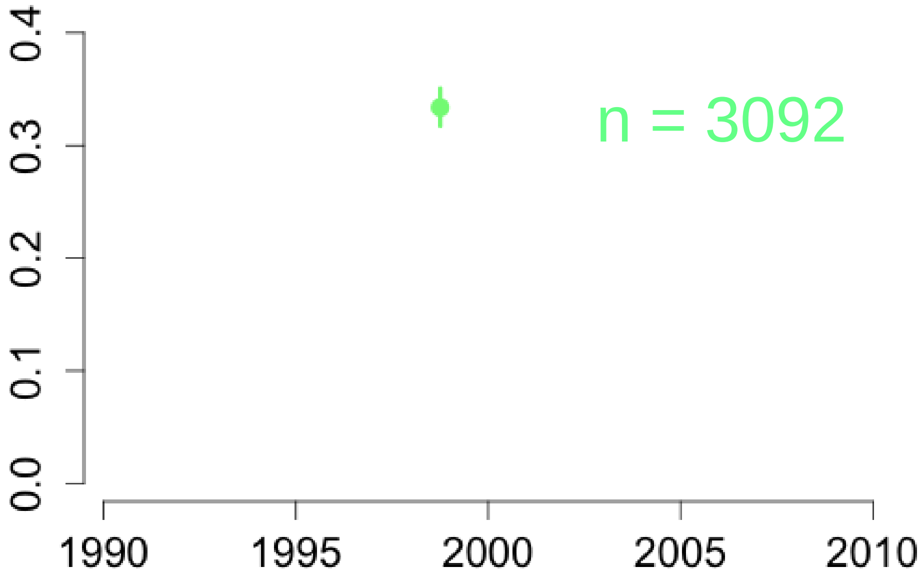
Deterministic models

Process Model

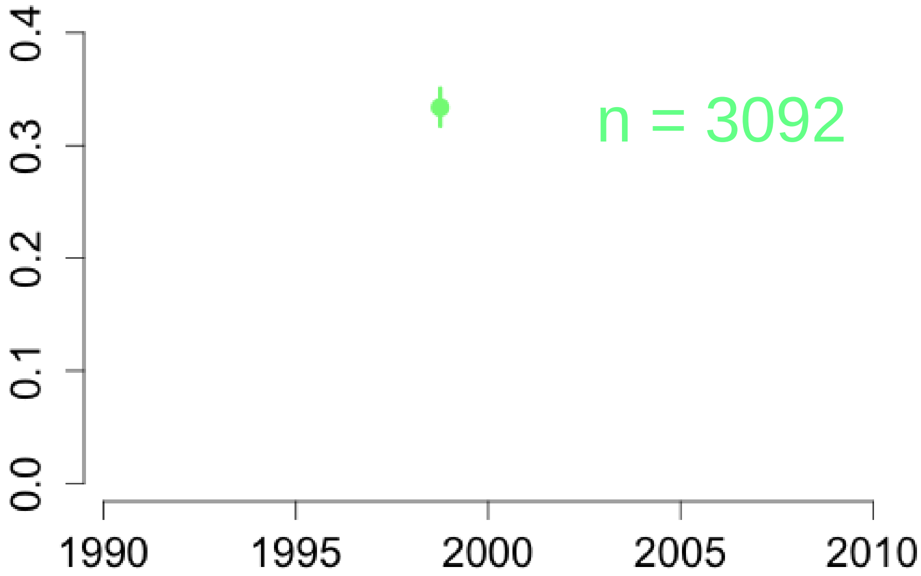



Parameters
some (possibly) fixed
and others to be fitted
Time series
expectation
or distribution of
latent variables
Deterministic models
Stochastic models
Process Model
S
I

Data



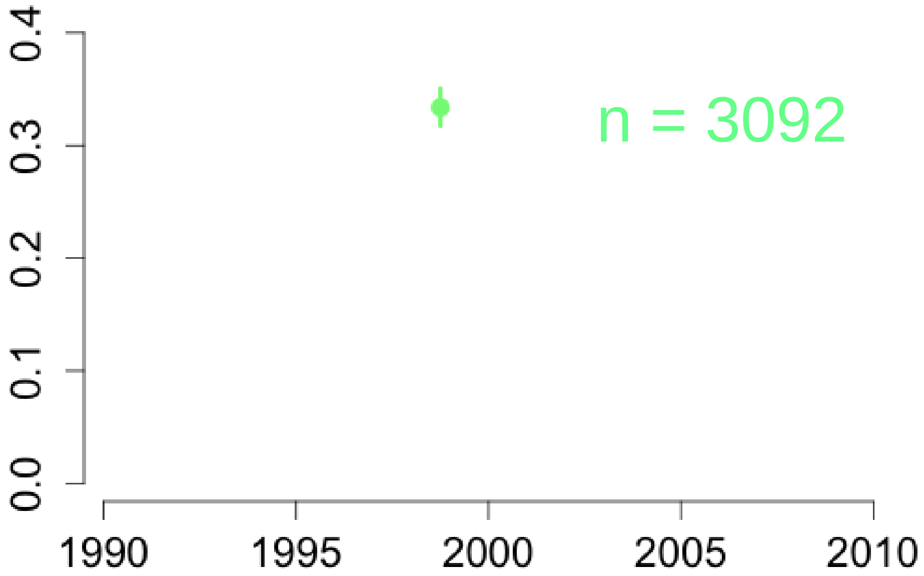
[Data]



Data

Observation model

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



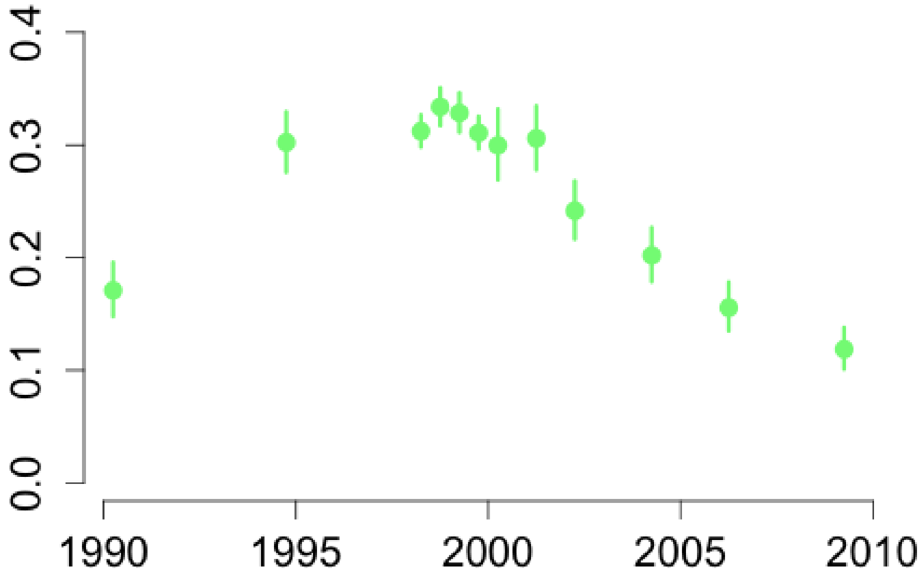
Data

Observation model

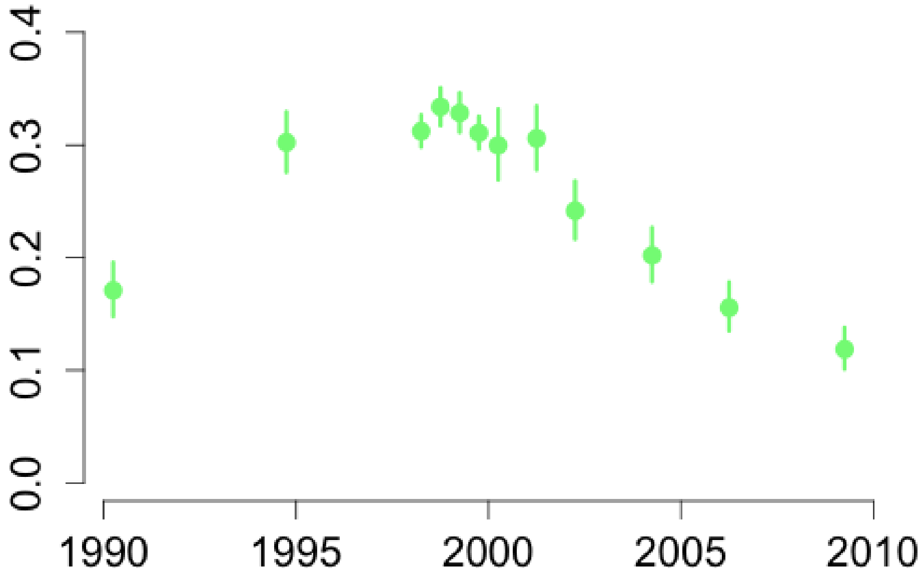
PDF: $$f(x \mid p) = \binom{n}{x} p^x (1-p)^{n-x}$$

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

Likelihood of prevalence (given data)



Data

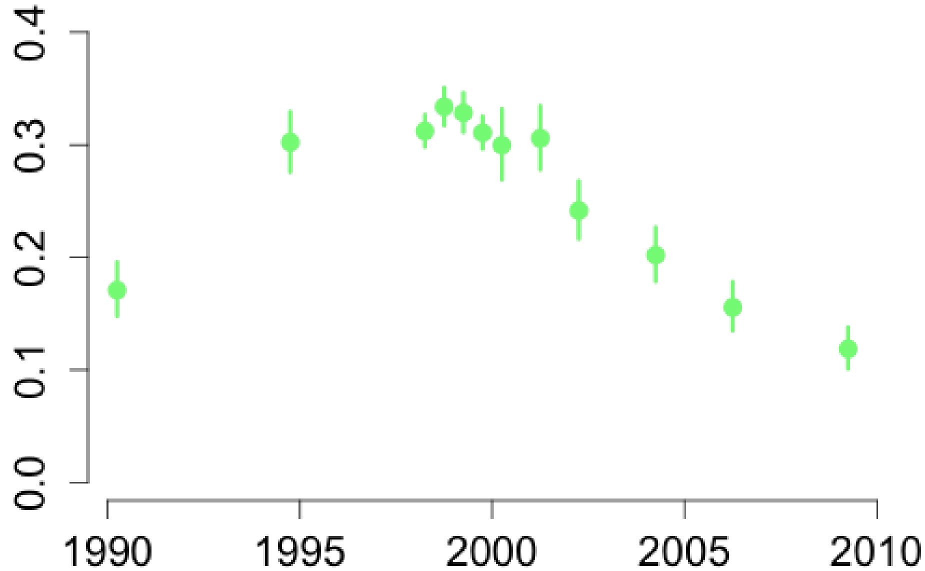


Data

PDF:

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

Observation model



Data

PDF:

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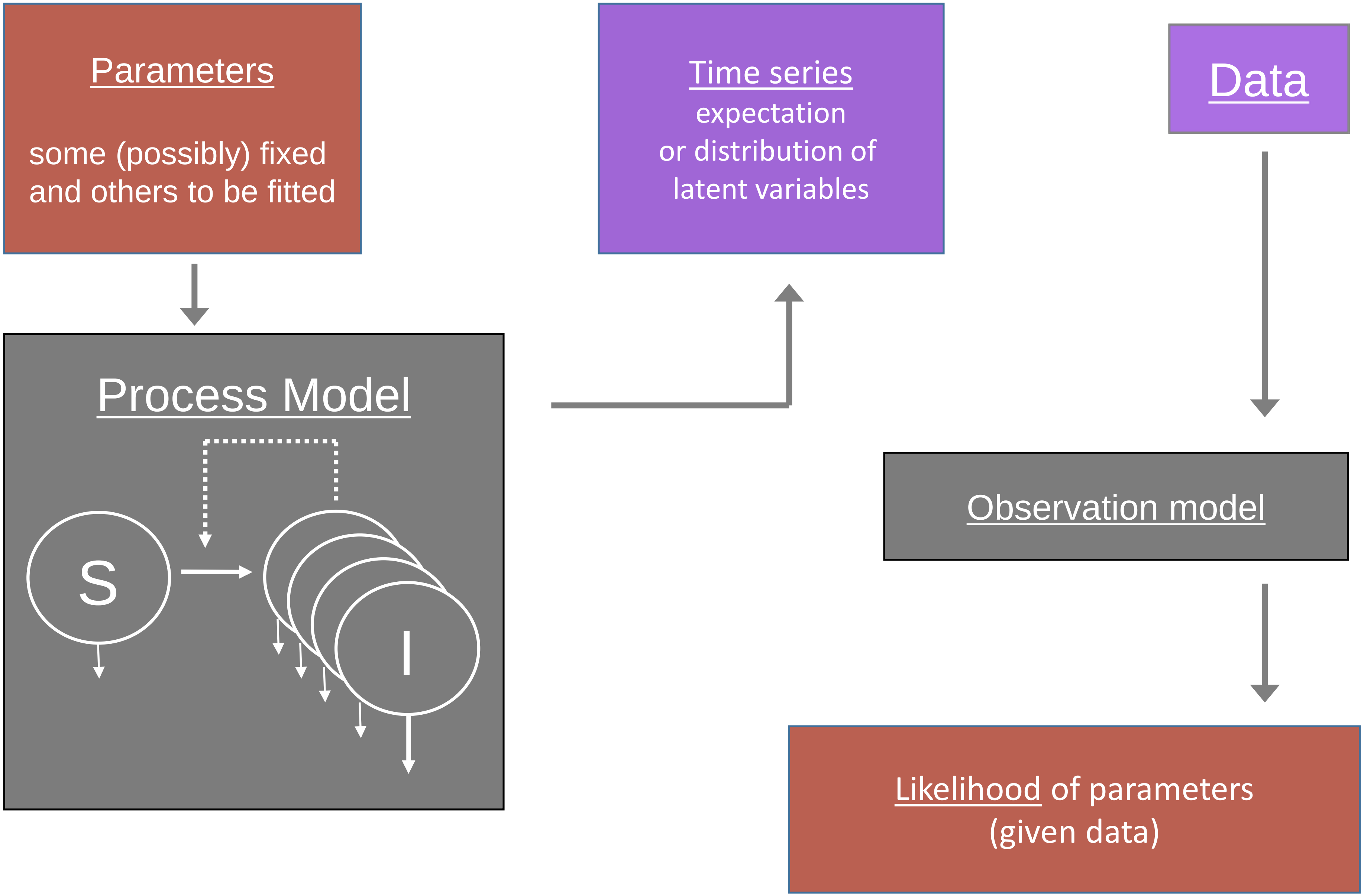
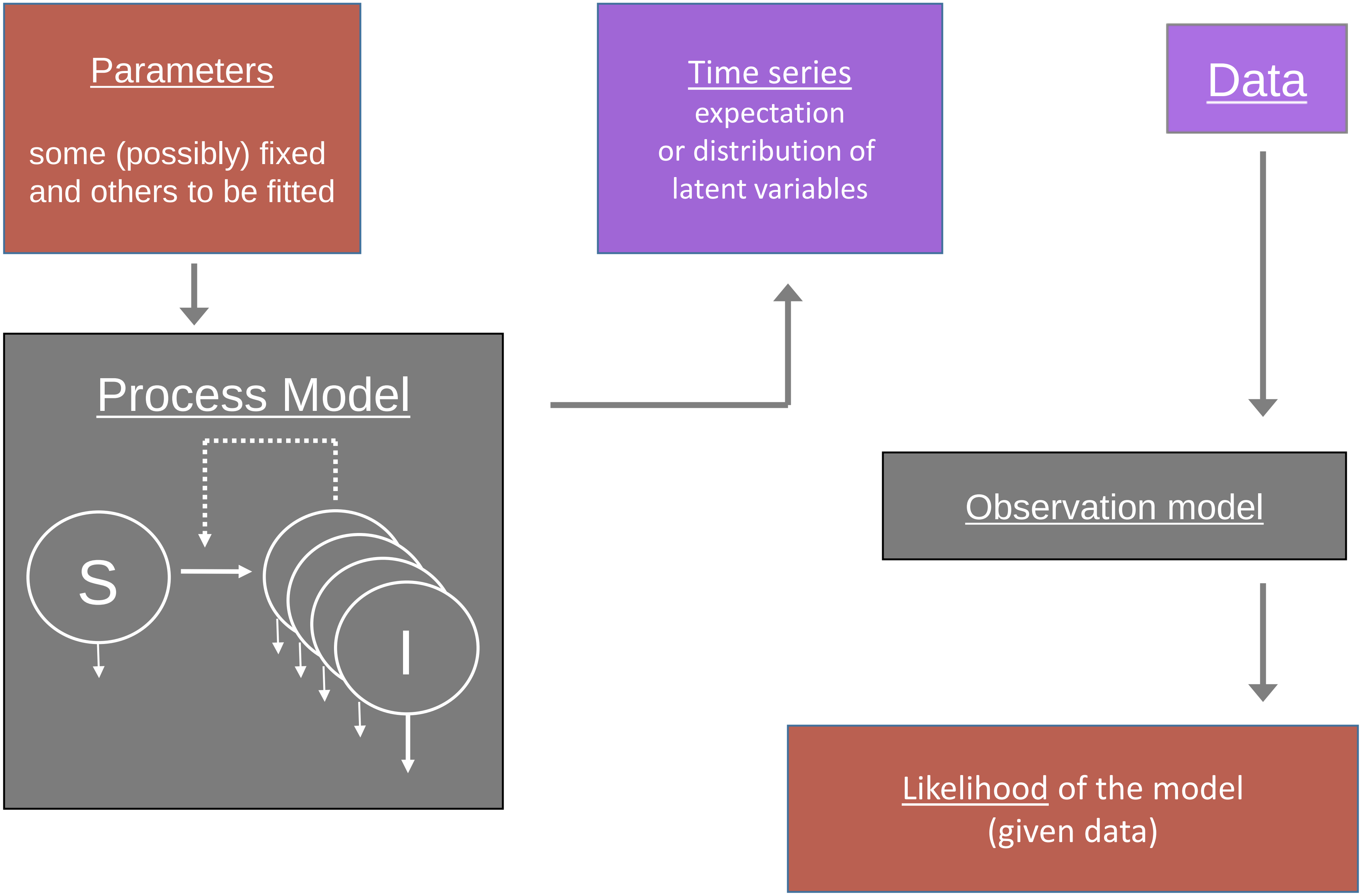
Observation model

LIKELIHOOD:

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

Likelihood of prevalence trajectory (given data)


Parameters
some (possibly) fixed
and others to be fitted
Process Model
S
I
Time series
expectation
or distribution of
latent variables
Data
Observation model
Likelihood of parameters
(given data)


Parameters
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Process Model
S
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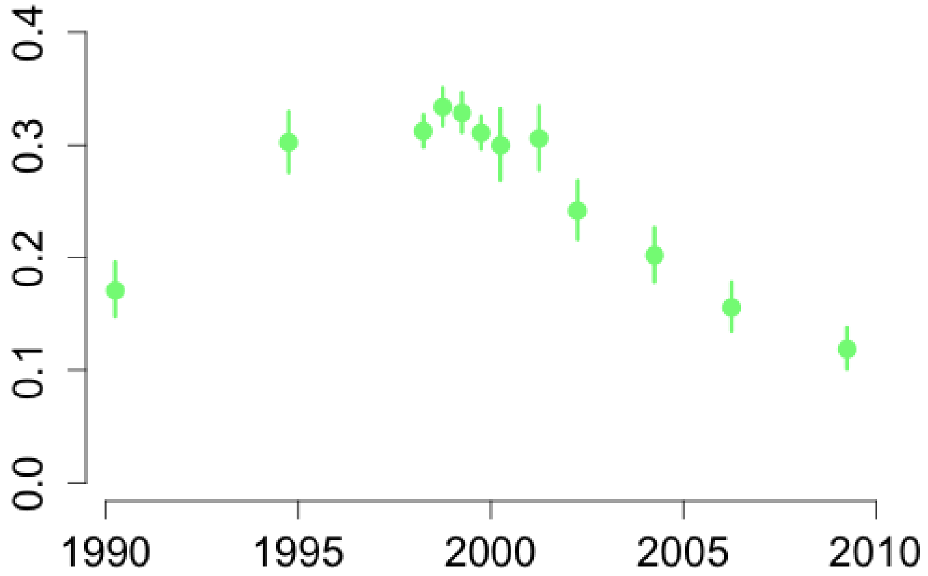
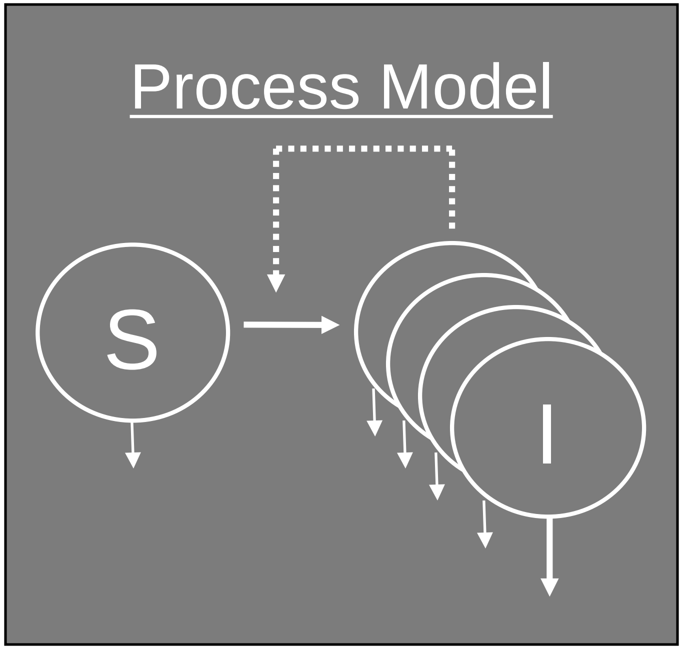
Time series
expectation
or distribution of
latent variables
Data
Observation model
Likelihood of the model
(given data)





Why do we fit models to data in infectious disease epidemiology?

Koopman's Inference Robustness Assessment Framework

Koopman’s Inference Robustness Assessment Framework

1. Select the policy inference to be pursued

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2. Construct & Analyze Simple Models

Koopman's Inference Robustness Assessment Framework

1. Select the policy inference to be pursued

2. Construct & Analyze Simple Models

3. Constrain Parameter Space with Data

Koopman's Inference Robustness Assessment Framework

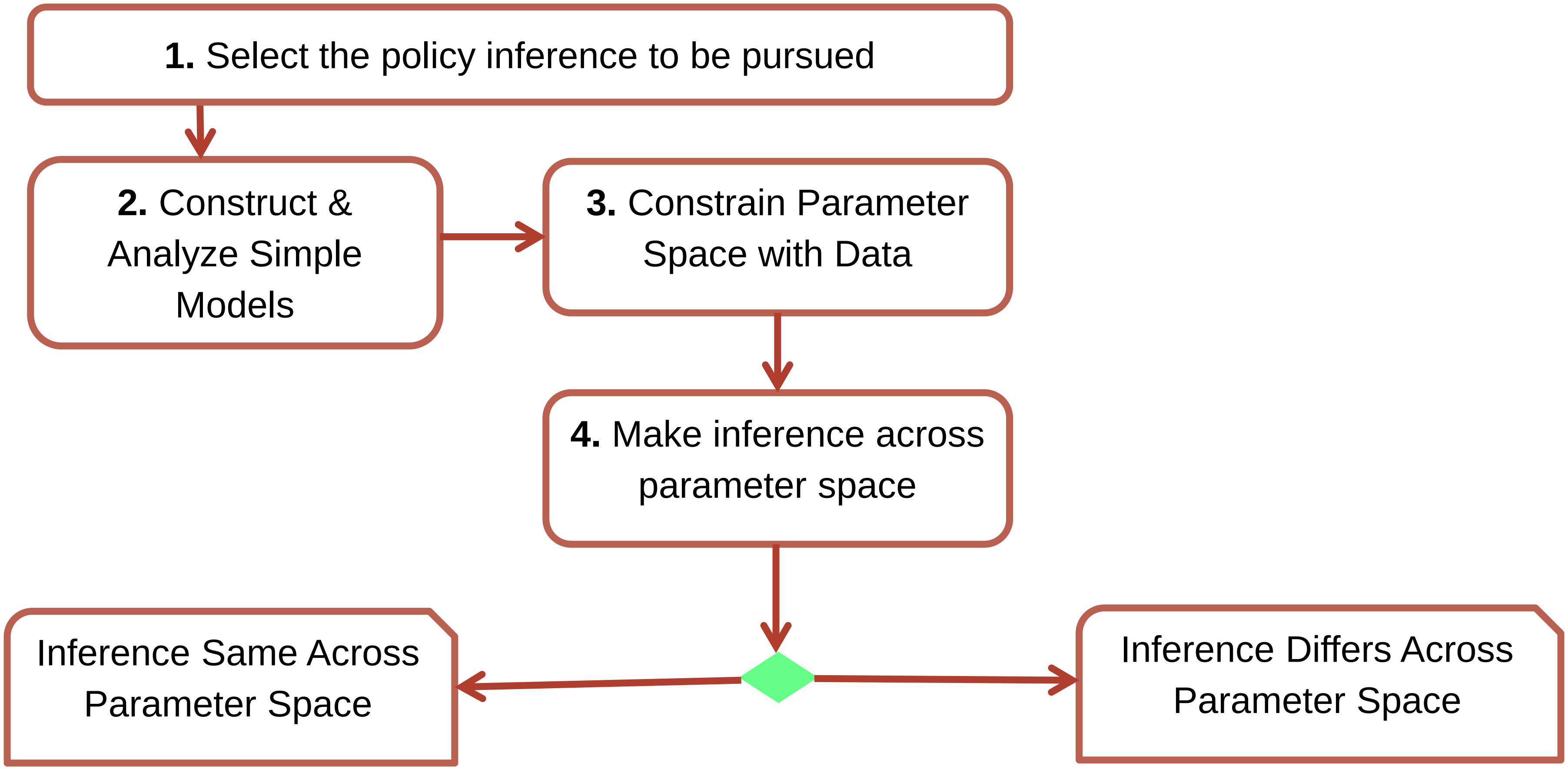
1. Select the policy inference to be pursued

2. Construct & Analyze Simple Models

3. Constrain Parameter Space with Data

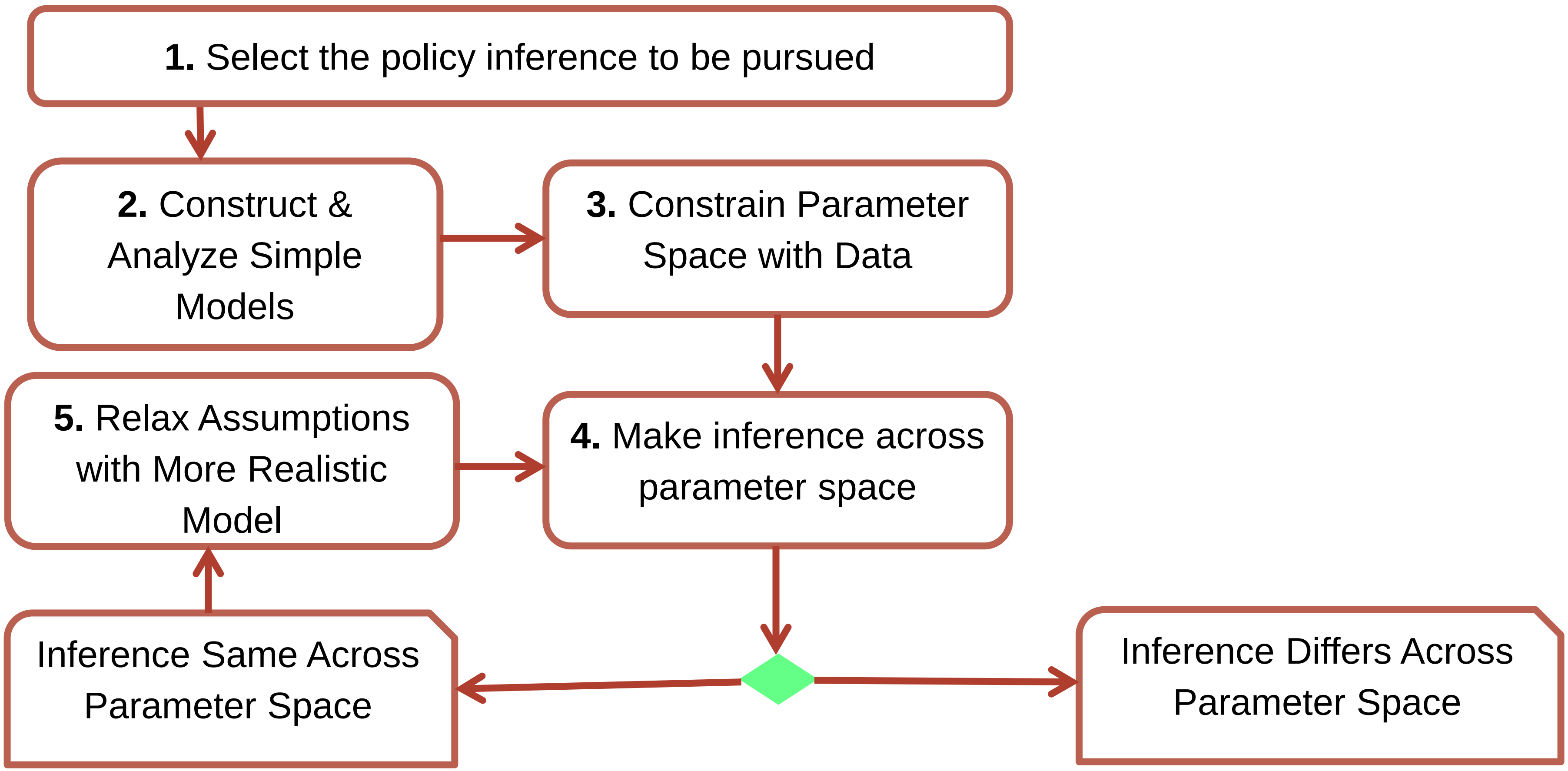
4. Make inference across parameter space

Koopman’s Inference Robustness Assessment Framework



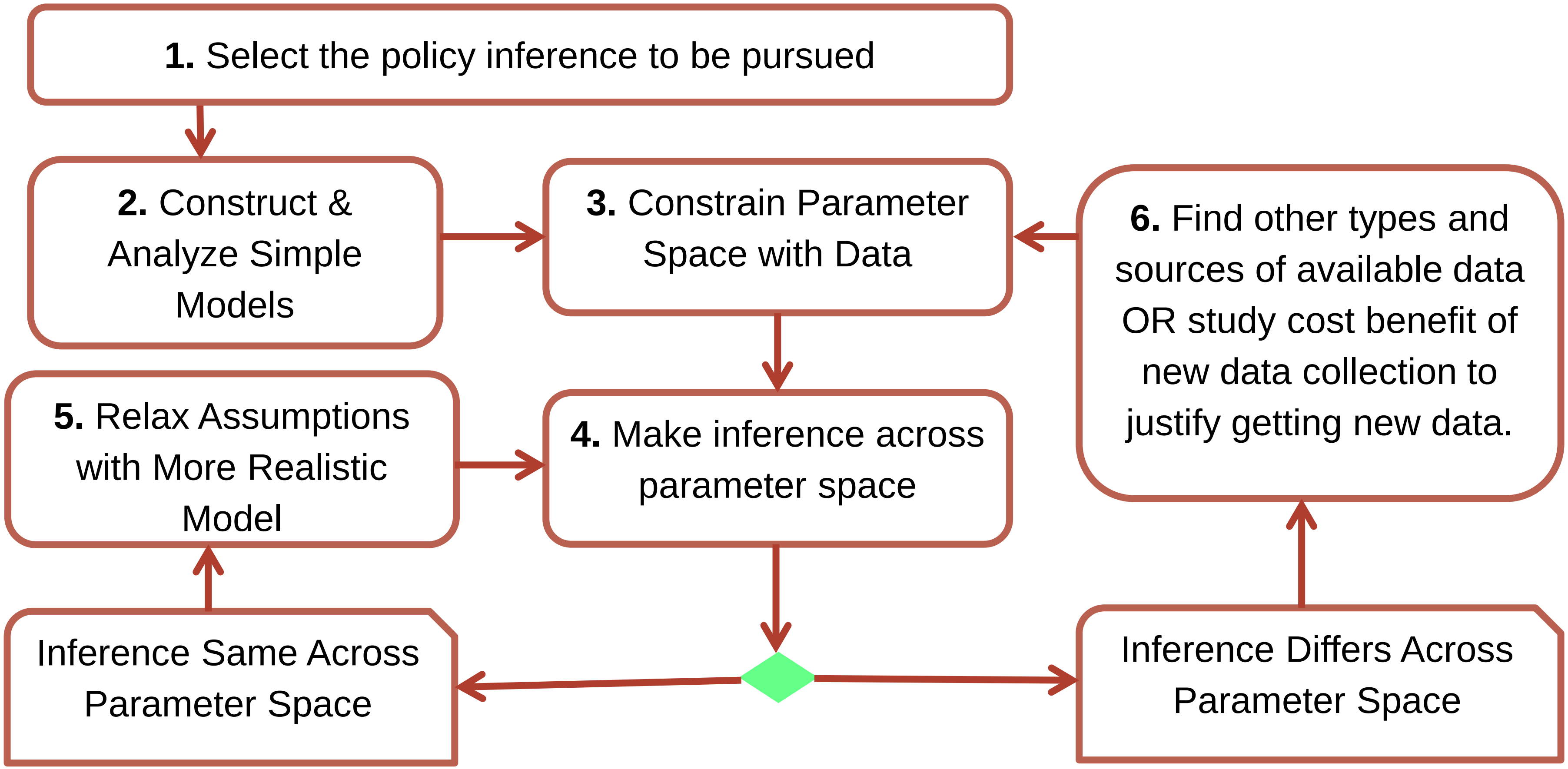
Koopman et al. 2014. Slide courtesy of JS Koopman (with modification).

Koopman's Inference Robustness Assessment Framework



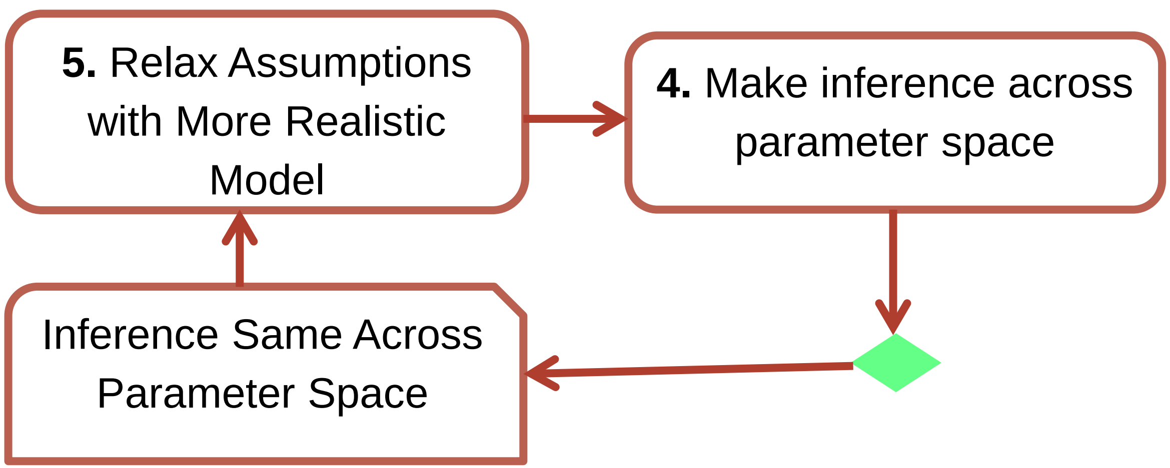
Koopman et al. 2014. Slide courtesy of JS Koopman (with modification).

Koopman's Inference Robustness Assessment Framework



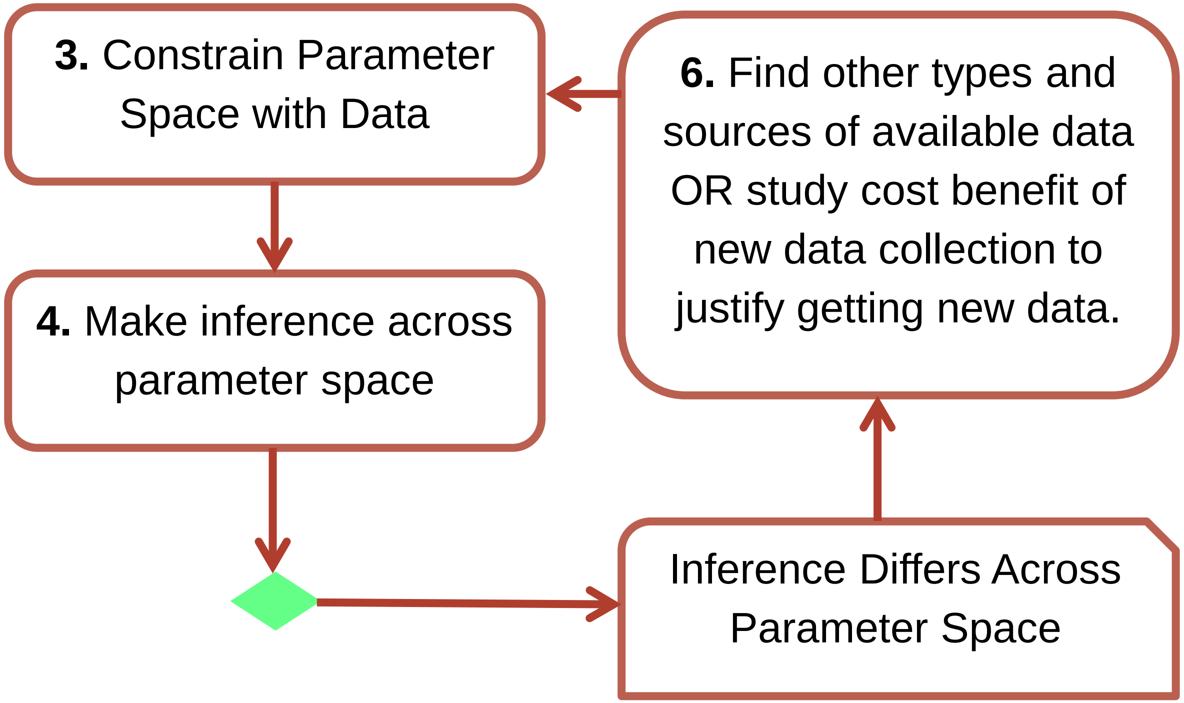
Koopman's Inference Robustness Assessment Framework

Inference **Robustness** Assessment Loop



Koopman's Inference Robustness Assessment Framework

Inference
Identifiability
Assessment
Loop



Koopman's Inference Robustness Assessment Framework

- Assess inference robustness to realistic relaxation of simplifying model assumptions

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- Pursue complexity that matters by keeping models as simple as possible but not ***so*** simple that they lead to an incorrect inference

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Validate the inference!

Koopman's Inference Robustness Assessment Framework

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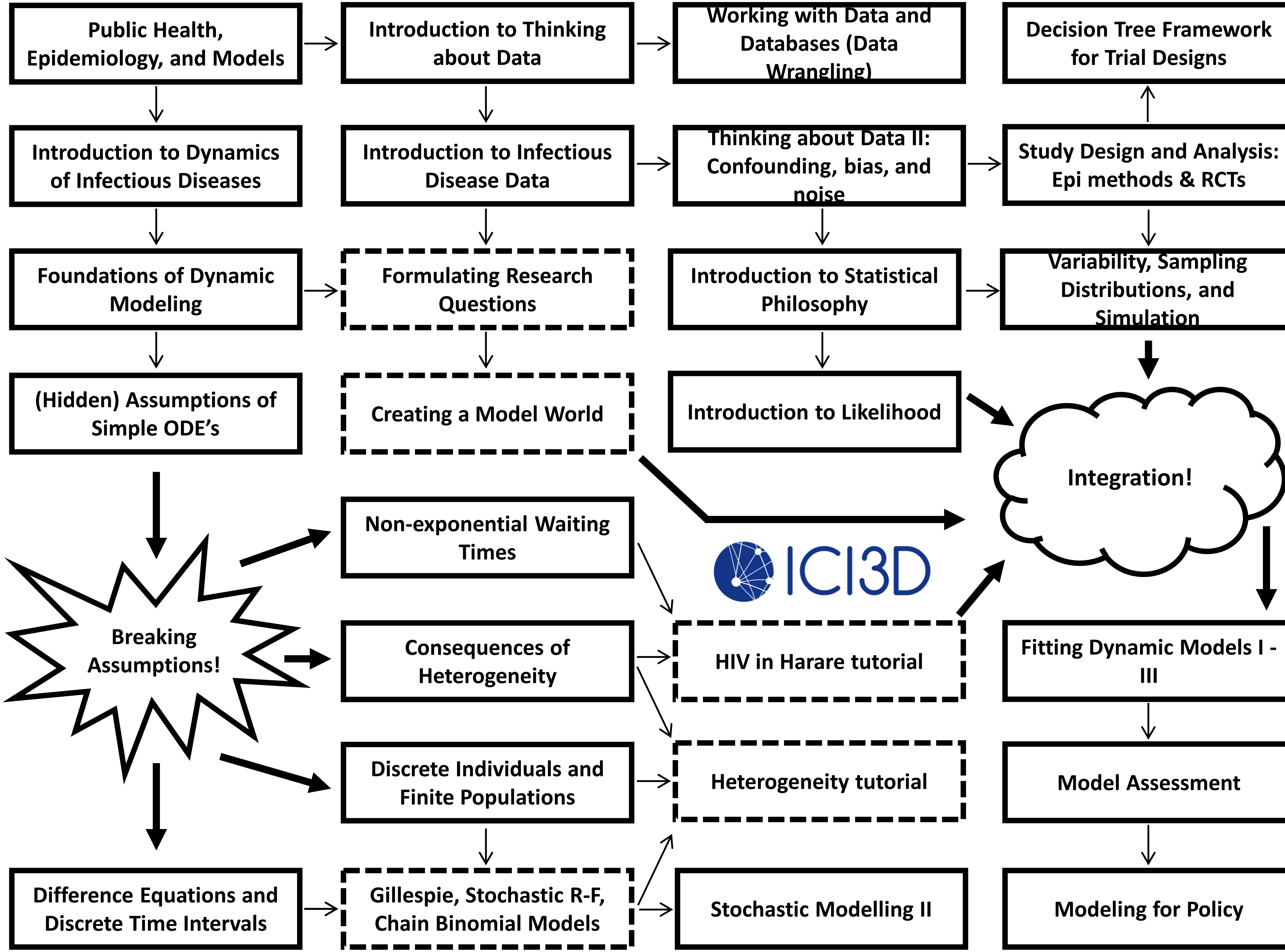
- Pursue complexity that matters by keeping models as simple as possible but not ***so*** simple that they lead to an incorrect inference

Validate the inference!

not (just) the model or method you're working with

Summary

- Model parameters can be estimated directly or fit to a dynamic model
- Integration of models and data is essential to make sure our models are grounded in the real world
- Simple models are easily understood but make strong assumptions
- Models can inform data collection priorities
- Add complexity gradually, to increase understanding and validate the policy inference


Public Health, Epidemiology, and Models
Introduction to Thinking about Data
Working with Data and Databases (Data Wrangling)
Decision Tree Framework for Trial Designs
Introduction to Dynamics of Infectious Diseases
Introduction to Infectious Disease Data
Thinking about Data II: Confounding, bias, and noise
Study Design and Analysis: Epi methods & RCTs
Foundations of Dynamic Modeling
Formulating Research Questions
Introduction to Statistical Philosophy
Variability, Sampling Distributions, and Simulation
(Hidden) Assumptions of Simple ODE's
Creating a Model World
Introduction to Likelihood
Integration!
Non-exponential Waiting Times
ICI3D
Breaking Assumptions!
Consequences of Heterogeneity
HIV in Harare tutorial
Fitting Dynamic Models I - III
Discrete Individuals and Finite Populations
Heterogeneity tutorial
Model Assessment
Difference Equations and Discrete Time Intervals
Gillespie, Stochastic R-F, Chain Binomial Models
Stochastic Modelling II
Modeling for Policy

Juliet R.C. Pulliam and Steve E. Bellan. 'Likelihood fitting and dynamic models, Part 1: Dynamic model fitting and inference robustness'. DOI:10.6084/m9.figshare.5044672

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