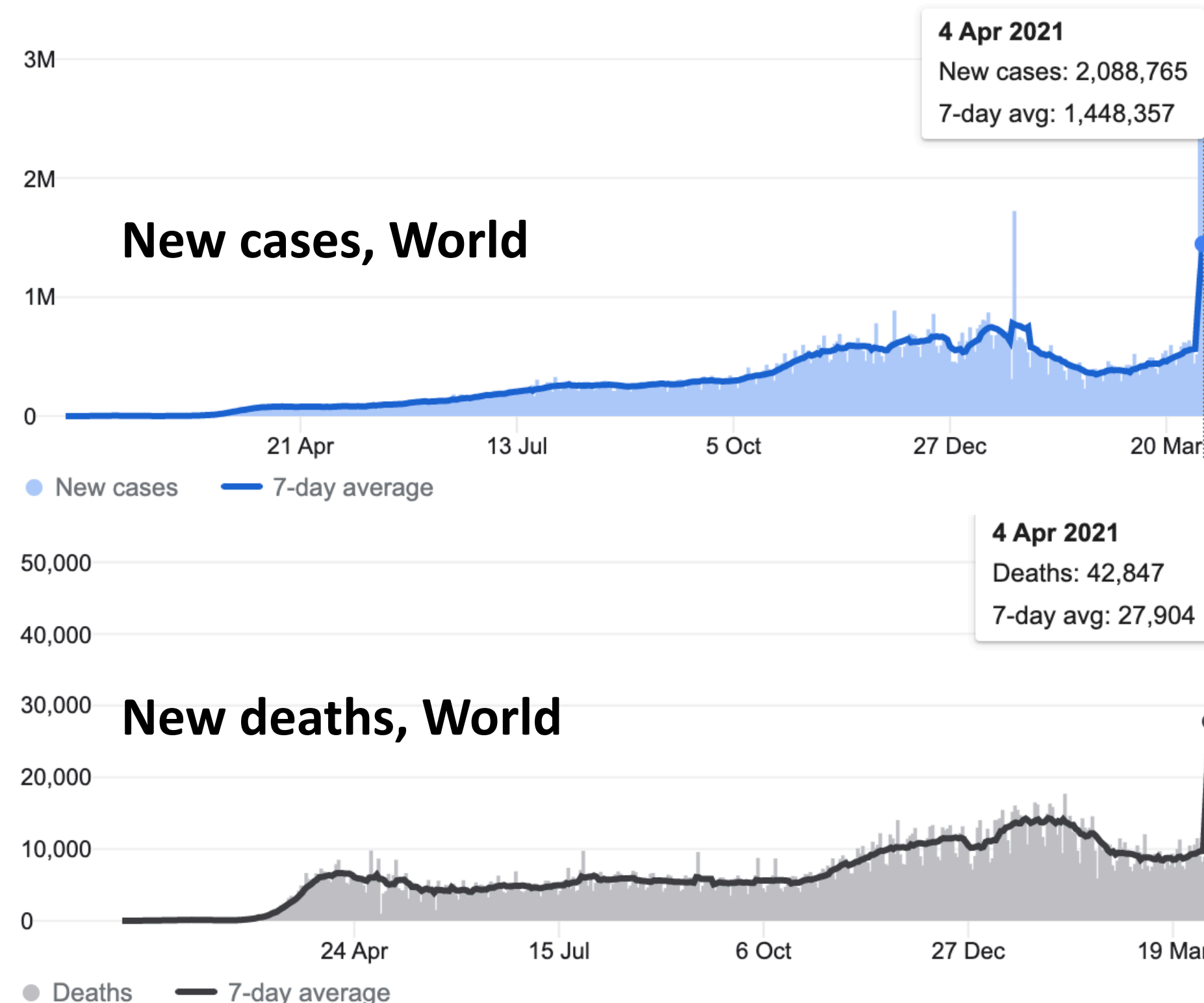


Epidemic Model Guided Machine Learning for COVID-19 Forecasts

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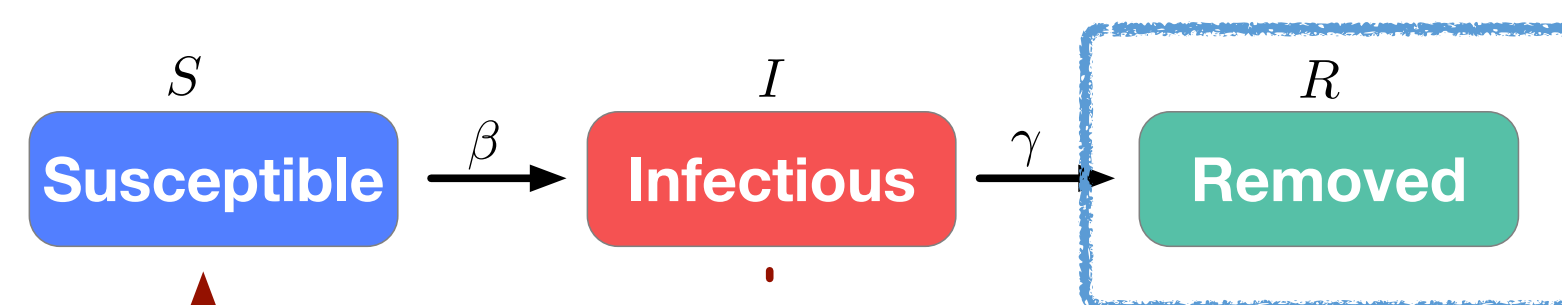
Severity of the Pandemic



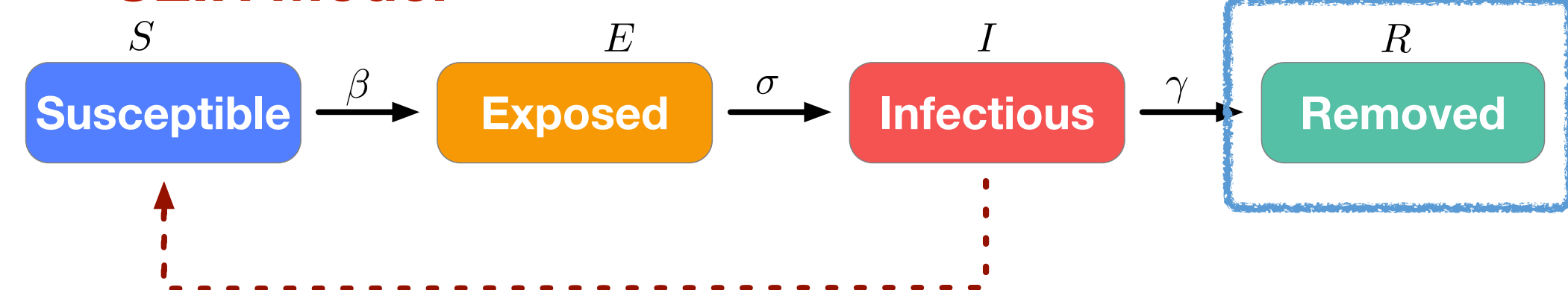
How to model the spread of the virus and make accurate forecasts for deaths and cases?

Conventional Epidemic Models

SIR Model



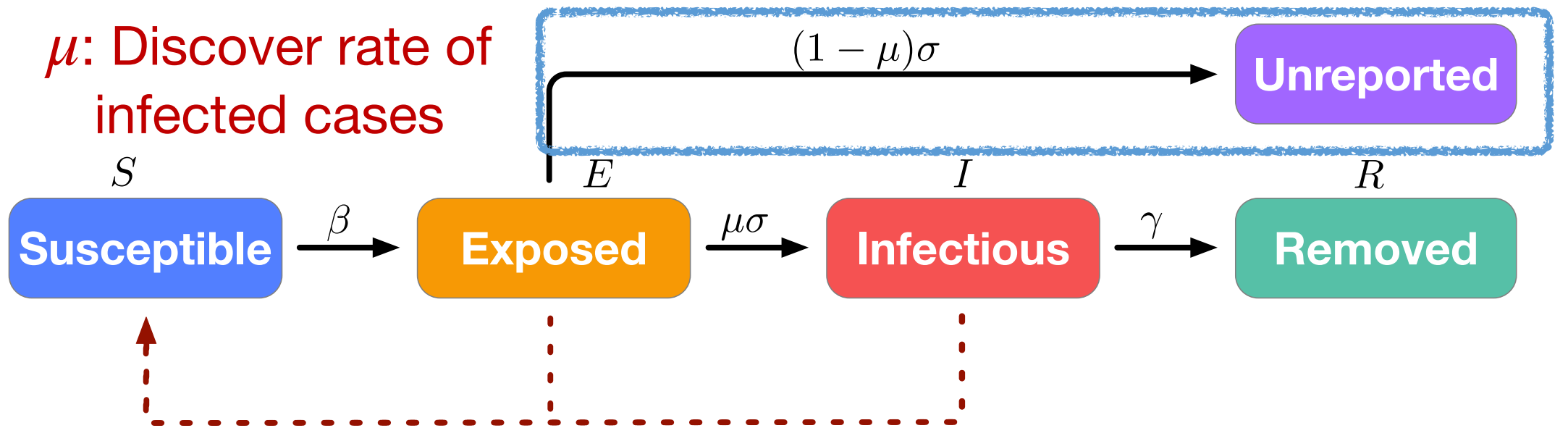
SEIR Model



β : Contact/Infectious rate σ : Incubation rate γ : Recover rate

Many exposed cases may not be tested and further reported to the public.

Our Model (SuEIR)



ODE Description

$$\frac{dS_t}{dt} = -\frac{\beta(I_t + E_t)S_t}{N}, \quad \frac{dE_t}{dt} = \frac{\beta(I_t + E_t)S_t}{N} - \sigma E_t$$

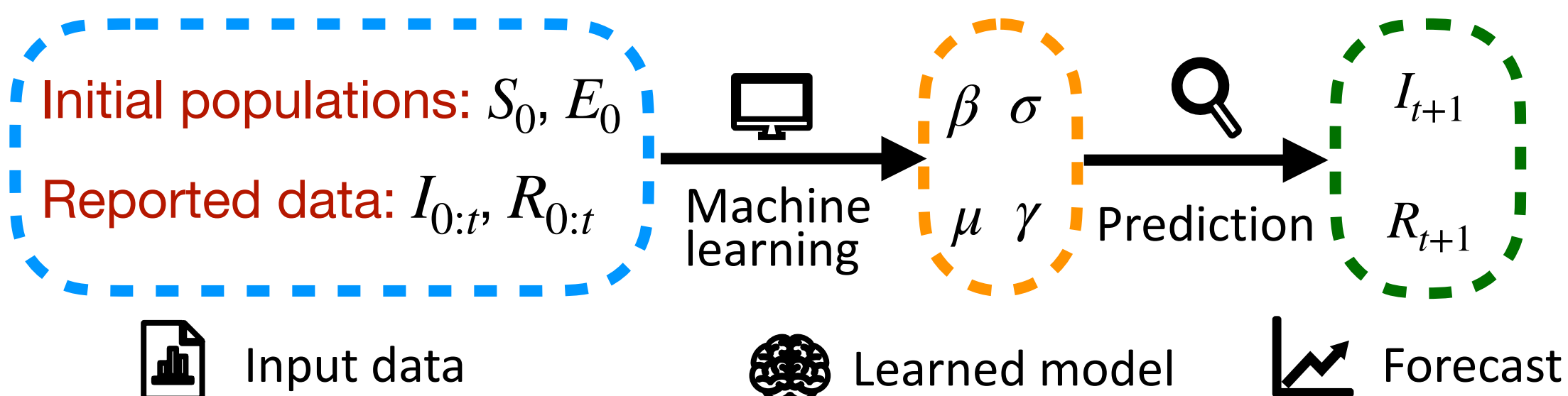
$$\frac{dI_t}{dt} = \mu\sigma E_t - \gamma I_t, \quad \frac{dR_t}{dt} = \gamma I_t$$

Basic reproduction number

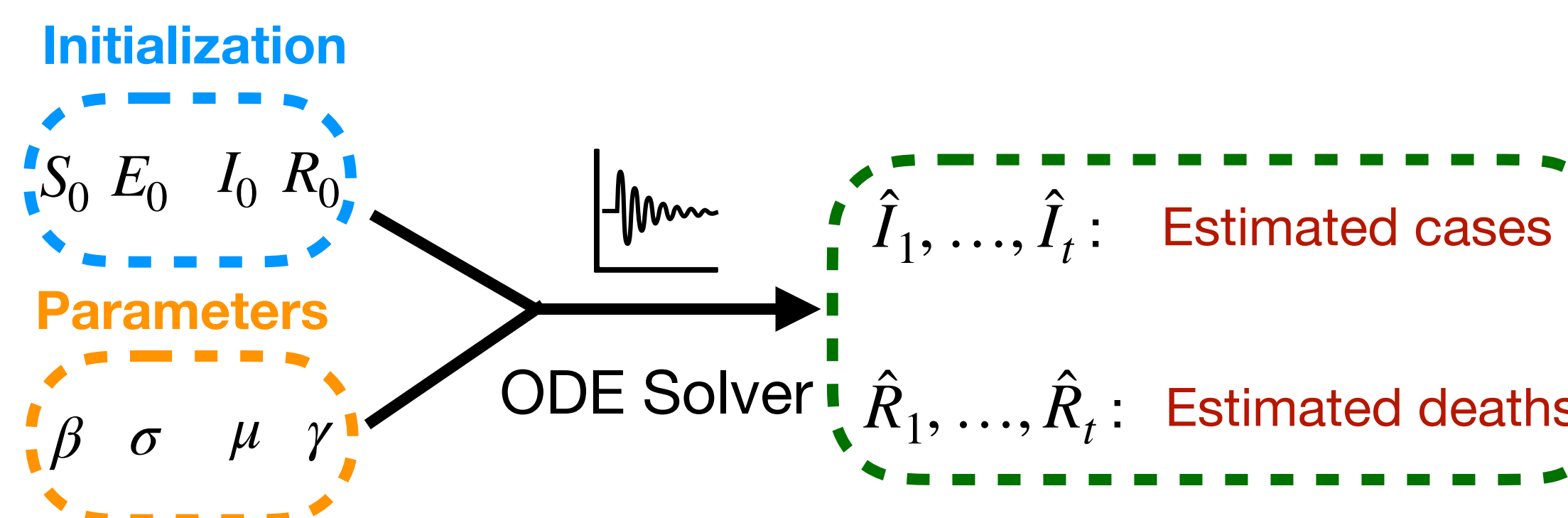
$$R_0 = \frac{\beta}{\sigma} + \frac{\beta\mu}{\gamma}$$

Machine Learning Framework

Machine Learning Pipeline



Learning Model Parameters



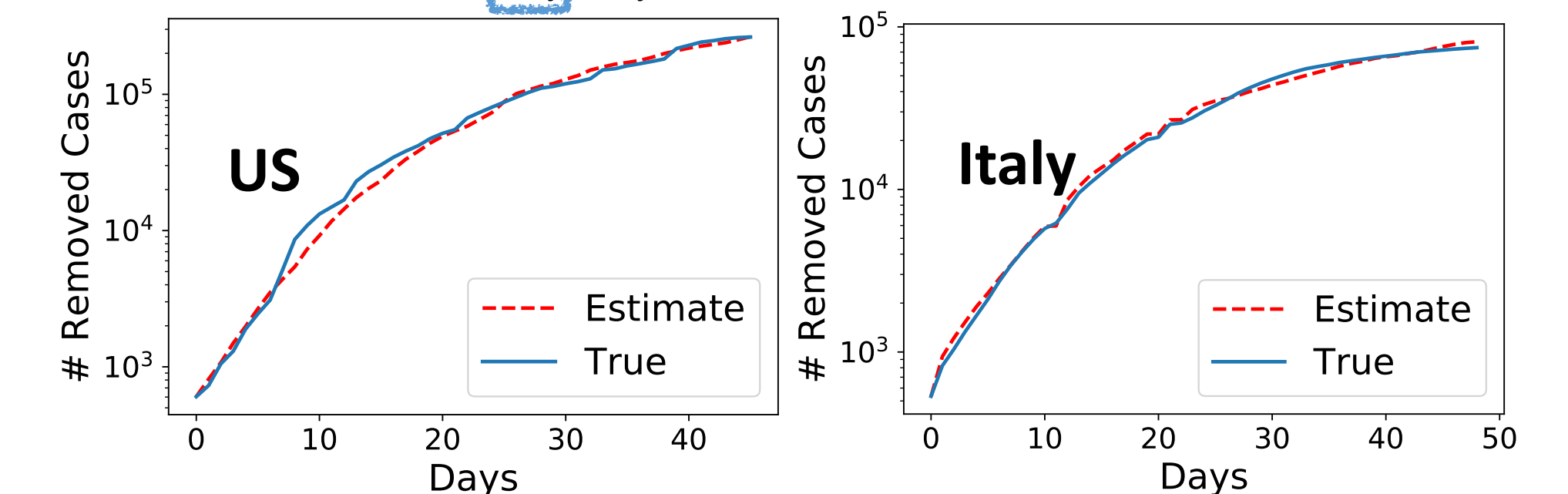
Loss Function

$$L(\beta, \sigma, \mu, \gamma; I_{1:T}, R_{1:T}) = \frac{1}{T} \sum_{t=1}^T [(\log(\hat{I}_t/I_t))^2 + (\log(\hat{R}_t/R_t))^2]$$

Implementation Details

Decomposition of Removed Cases

Fatality cases $F_t/R_t = a \exp(-bt) + c$



Validation

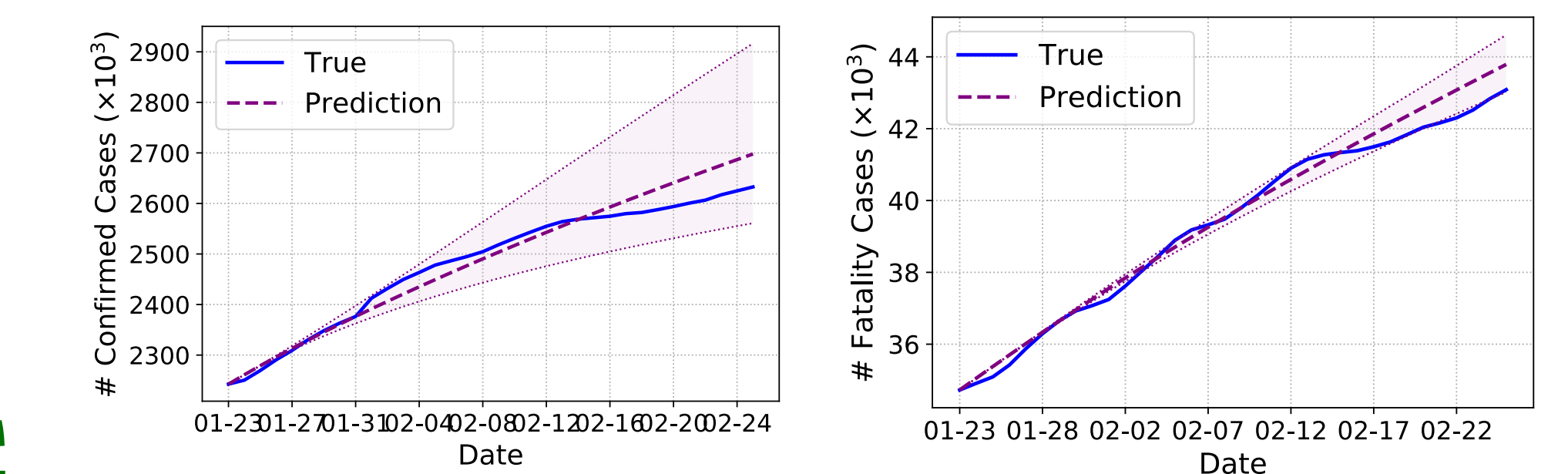
We try different initial guesses S_0, E_0 and select the model with smallest validation risk.

Modeling the Resurgence

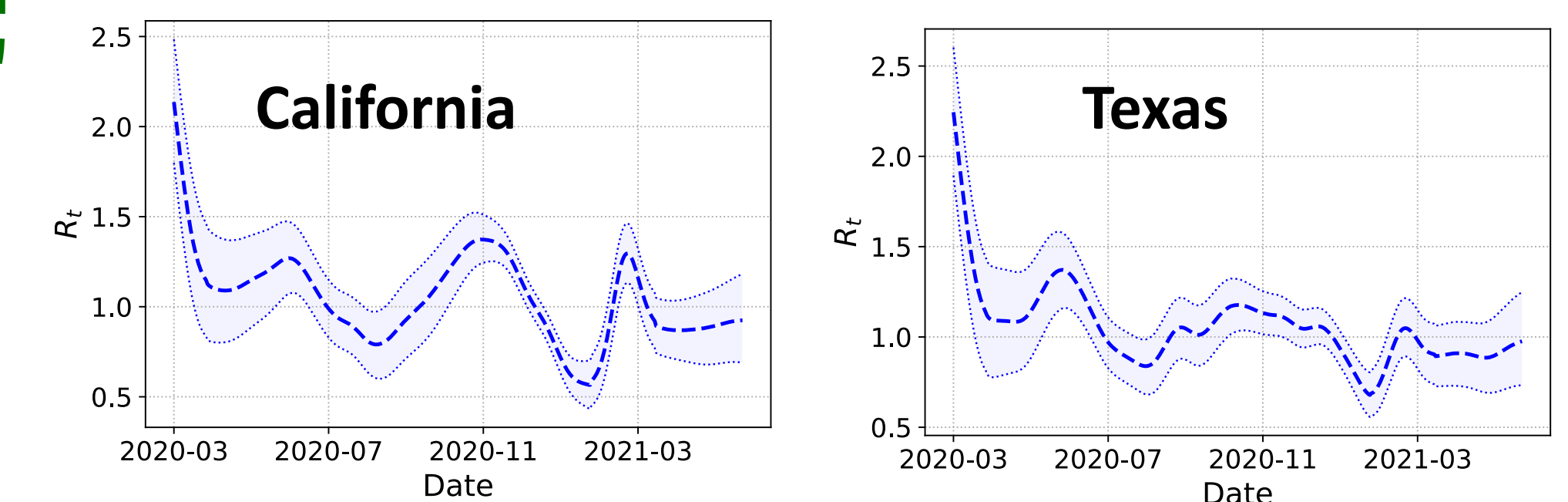
- We split the training period into multiple stages and train multiple SuEIR models separately.
- Susceptible populations are assumed to increase after the resurgence date.

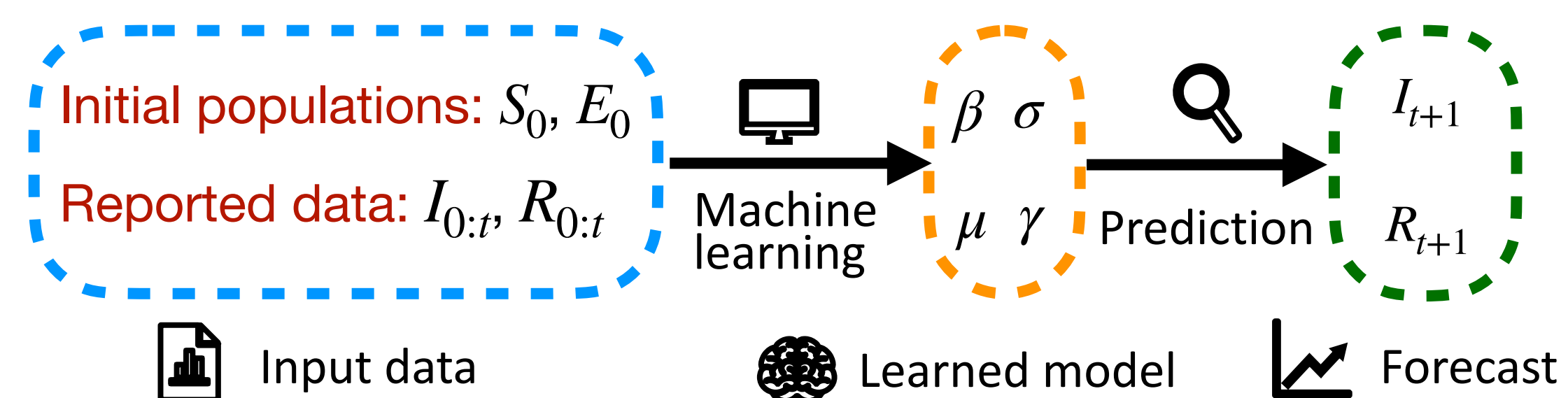
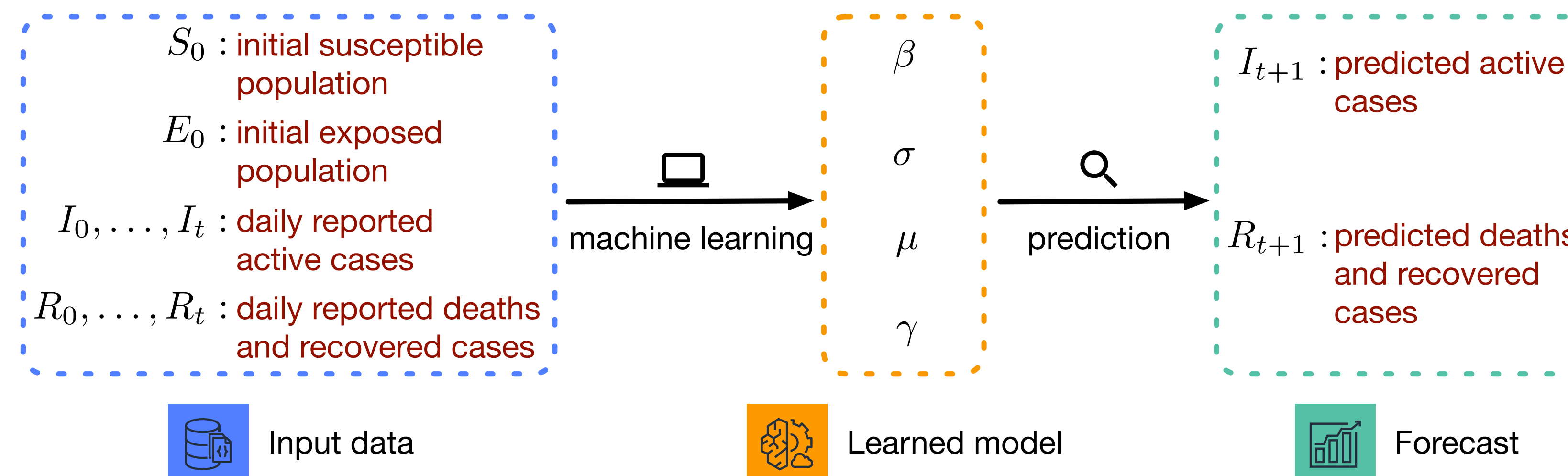
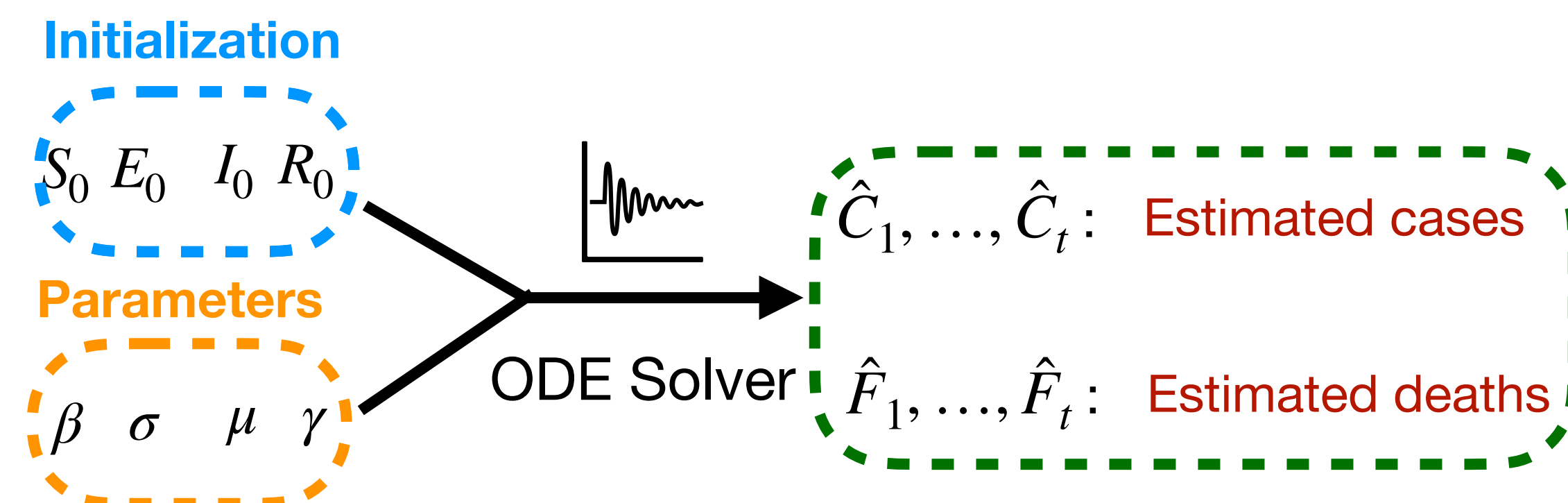
Forecasts and Reproduction Numbers

Forecasts (Texas)



Reproduction Numbers





$$L(\theta; I_{1:T}, R_{1:T}) = \frac{1}{T} \sum_{t=1}^T \left[\left(\log(\hat{I}_t / I_t) \right)^2 + \left(\log(\hat{R}_t / R_t) \right)^2 \right]$$