

# Parameterizing a Type 1 Diabetes ODE Model

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# outline

- what is the t1d model?
  - Why is this model useful
    - developing potential treatments - Rachel : )
  - what is diabetes onset - Daniel : )
  - what is the structure of the model? - Maya : )
  - what is the overall goal? - Christina : )
- what does it mean to parameterize
  - what are the parameters vs. variables - TEAM 2
  - slide about differences/similarities
    - why would we use these two methods
    - combine two methods - TEAM 1
  - 2 ways - example based explanation (less math)
    - Kalman filters - TEAM 2
    - MCMC - TEAM 1
- (Lotka Volterra?)

# Type 1 diabetes

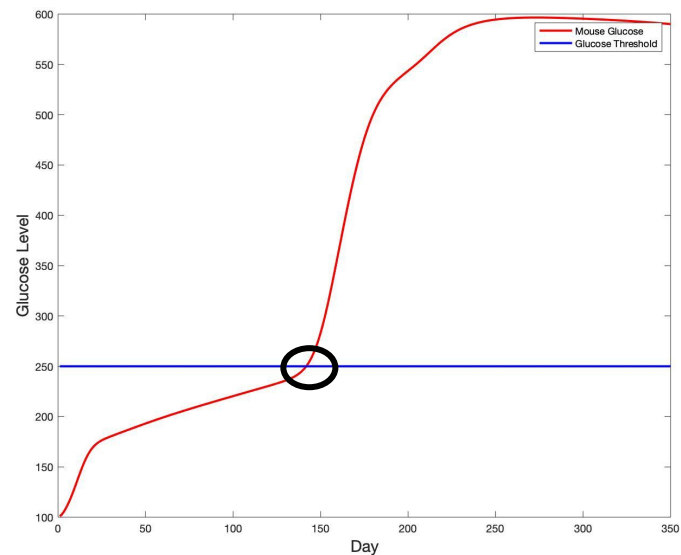
- Autoimmune disease characterized by inability to regulate blood glucose
- Can be managed, but no cure
- *Apoptotic wave* during early development cause immune response, ability to respond determines diabetes onset

# Why model T1D?

- Modeling T1D helps give us a better understanding of the progression of the disease, which can be useful in determining possible treatments
- Using the model, we can simulate possible treatments and see determine whether or not we expect them to be successful
- This is especially helpful for treatments that are time sensitive

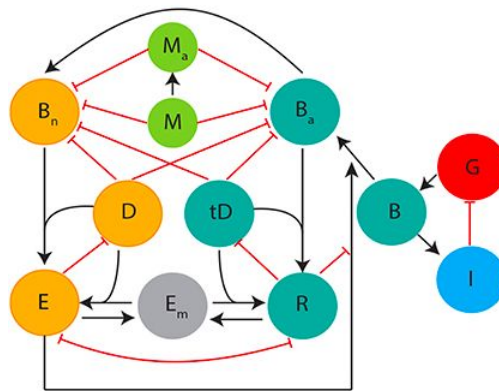
# Diabetes Onset

- Onset determined by Glucose levels
  - In mice, threshold ~ 250 mg/dl
- Various theories about what causes onset
  - Model uses apoptotic wave



# T1D Model

- 12 equation nonlinear ODE system
  - models immune cell interactions & relationships
- Time-dependent
- Bistable system:
  - healthy vs. disease state
  - transition determined by immune cell interactions
- Single compartment model – pancreas
- Non-obese diabetic (NOD) mice
- Glucose data – easy to collect



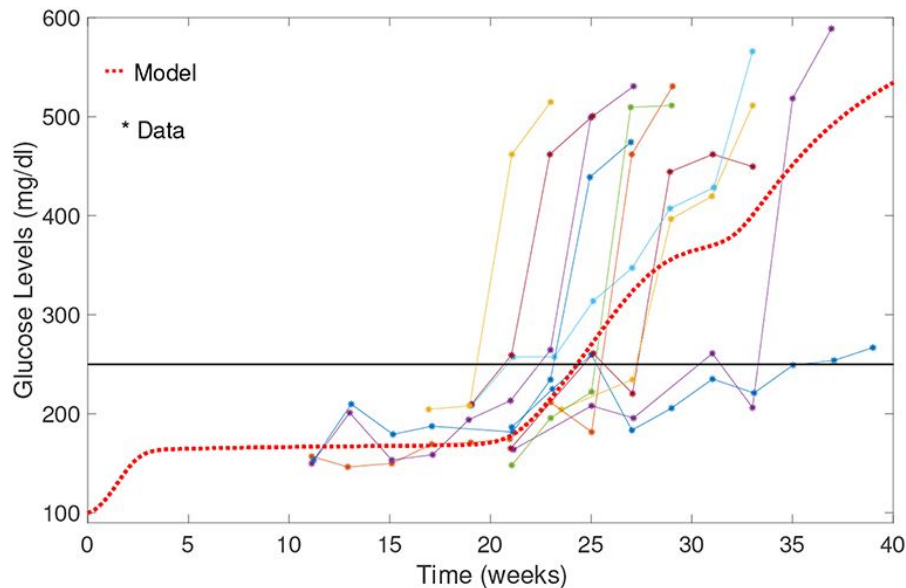
Variable	Description
B	Healthy $\beta$ -cell population
B <sub>a</sub>	Apoptotic $\beta$ -cell population
B <sub>n</sub>	Necrotic $\beta$ -cell population
D	Immunogenic DC population
tD	Tolerogenic DC population
E	Effector T cell population
E <sub>m</sub>	Memory T cell population
R	Regulatory T cell population
Ma	Active macrophage population
M	Macrophage populations
G	Glucose levels
I	Insulin levels

*Shtylla et al. 2019. A Mathematical Model for DC Vaccine Treatment of Type 1 Diabetes*

# Goal

- In paper:
  - Most parameters estimated from existing literature
- Accuracy is important
  - Parameters sit 'on the edge'
  - Very sensitive
- Explain varying mouse behavior
  - Progressive vs. acute

Task: Use MCMC and Unscented Kalman Filters (UKF) to estimate parameters for system based on observed glucose in mice



# What Does it Mean to Parametrize

- Differential equations are made up of variables and parameters
  - Variables are states within the system that change
  - Parameters are constants within the system

Example: In the differential equation

$$dx/dt = ax^2 + bx$$

$x$  is a variable and  $a$  and  $b$  are parameters.

- Often, when you are trying to create a model for a biological phenomena, the parameters are not known
- Parameterizing is the process of trying to find the parameters that best fit a model
- Often, this process involves comparing model predictions of a phenomena to actual observations



# Why Use Two Methods?

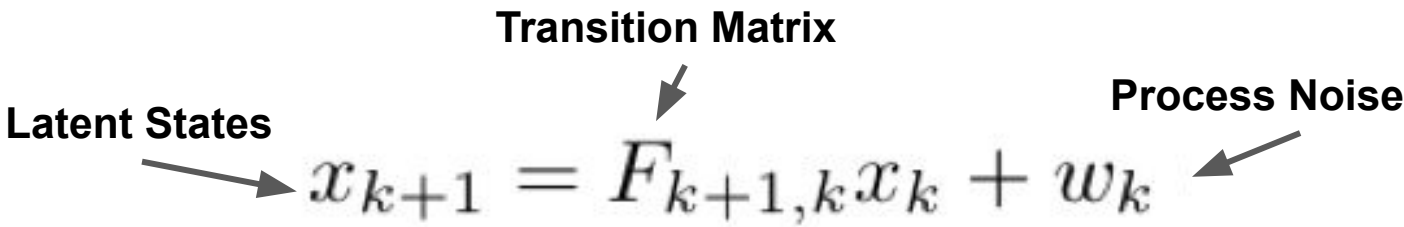
- MCMC
  - Bayesian approach, all data known at start
  - Parametrization on population level
  - Parameter distributions
- Kalman Filters
  - Adaptive, learns data point by data point
  - Parametrization on individual mouse level
  - Single parameter set
- *Potential to compare, combine methods*

# Kalman Filter General Idea

- Discrete time, state space model
- Two sets of data: **latent states ( $x$ )** and **observables ( $y$ )**
  - a. What I want to know versus what I do know
- Two step algorithm
  1. Propagate forward in time using knowledge of system
  2. Use observable to update estimate and system parameters
    - a. “How well did we do? How can we improve for next time?”
- Tunable model set up
  - Noise, covariances

# Modeling the System

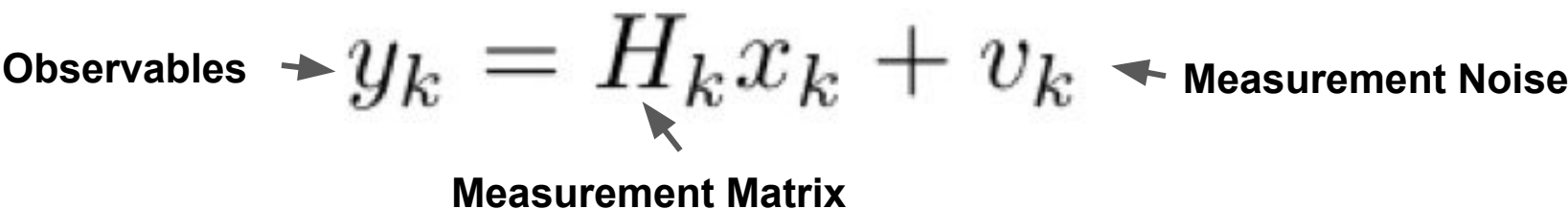
Latent States      Transition Matrix      Process Noise



$x_{k+1} = F_{k+1,k} x_k + w_k$

Detailed description: This diagram shows the state transition equation. The label 'Latent States' has an arrow pointing to the state variable  $x_{k+1}$ . The label 'Transition Matrix' has an arrow pointing to the matrix  $F_{k+1,k}$ . The label 'Process Noise' has an arrow pointing to the noise term  $w_k$ .

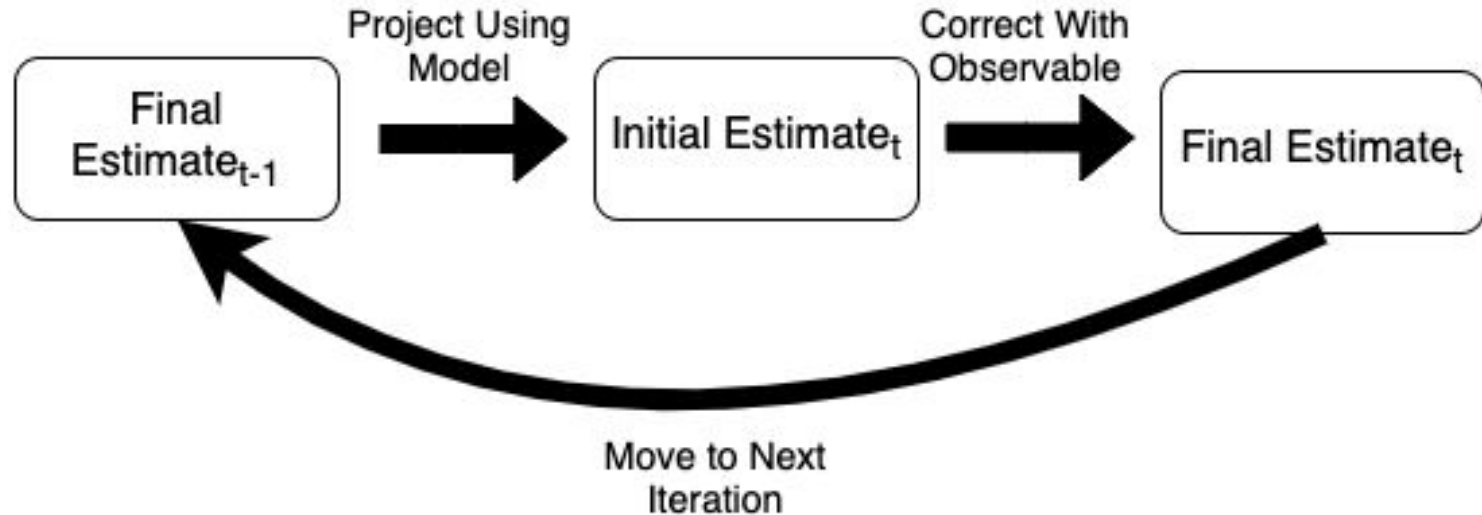
Observables      Measurement Matrix      Measurement Noise



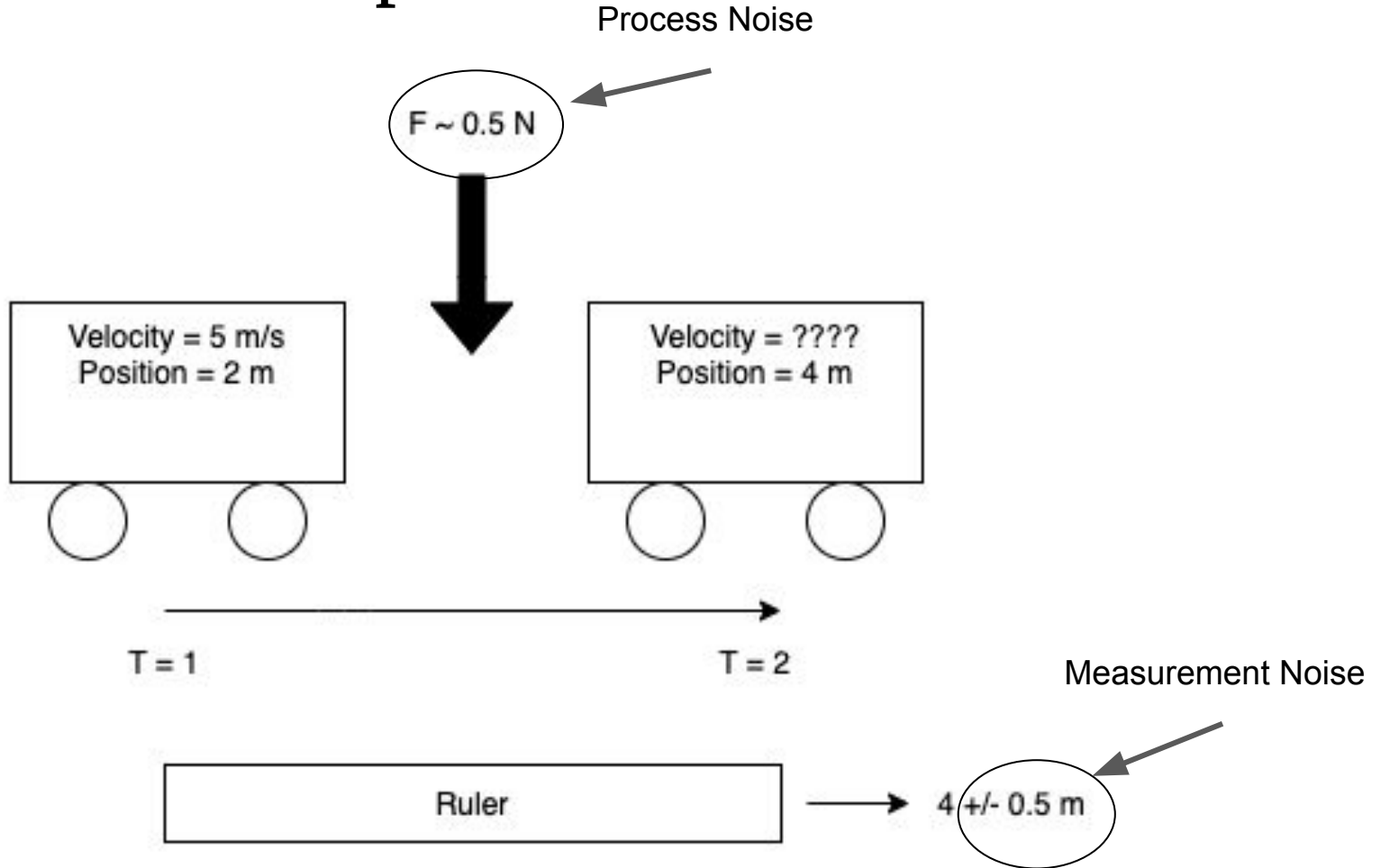
$y_k = H_k x_k + v_k$

Detailed description: This diagram shows the measurement equation. The label 'Observables' has an arrow pointing to the observation variable  $y_k$ . The label 'Measurement Matrix' has an arrow pointing to the matrix  $H_k$ . The label 'Measurement Noise' has an arrow pointing to the noise term  $v_k$ .

# Big Picture Diagram



# Kalman Filter Example



# Markov Chain Monte Carlo (MCMC)

- Parameter estimation based on maximum likelihood
  - Bayesian inference
- General idea
  - Propose parameters sets (*Markovian*)
  - Accept 'good' proposals
  - Reject 'bad' ones
  - Build a distribution of accepted 'good' parameters (*Monte Carlo*)

# Bayes' Theorem

$$P(\theta|D) = P(\theta)P(D|\theta)$$

$P(\theta)$  - prior

$P(D|\theta)$  - likelihood

$P(\theta|D)$  - posterior

$D$  - data

$\theta$  - parameter set

In terms of parameterization...

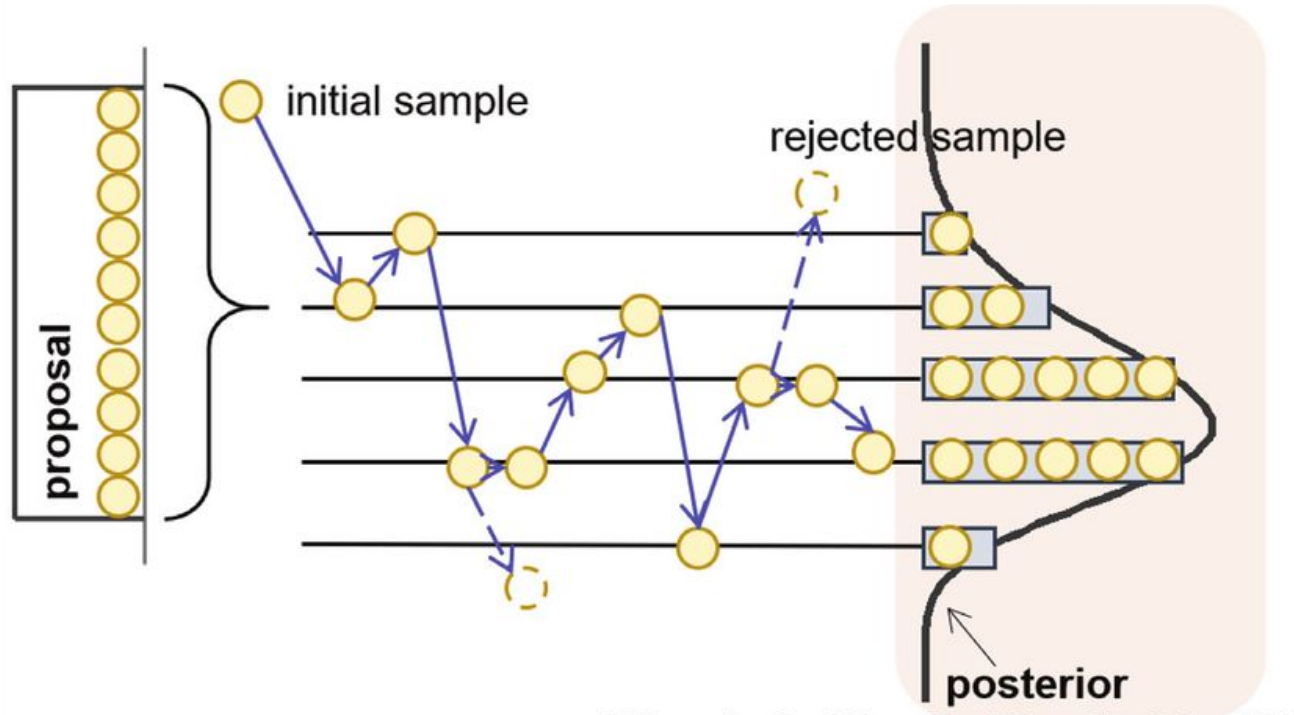
- *posterior* = estimated/sampled parameters
- *likelihood* = relationship between data points (noise)
  - tells us *how* to sample
- *prior* = knowledge about seeing parameters *before* seeing data
  - uninformative (uniform)
  - informative
- *proposal* = sampling distribution of parameter values

# Metropolis–Hastings

1. Choose  $\theta^0$  (initial guess for parameter values)
  - calculate posterior
2. For each iteration of the Markov Chain:
  - Sample candidate  $\theta^*$  from proposal distribution
    - calculate posterior
  - Accept or reject the proposed  $\theta^*$  based on the value of a **ratio**
    - $\rho = \frac{\text{posterior of } \theta^*}{\text{posterior of current } \theta}$       if  $\rho \geq 1$ : accept the transition  
if  $\rho < 1$ : only accept with a probability of  $\rho$
3. Stop sampling after sufficient # of samples (10,000 typical)
4. Compute pdf of parameters using MCMC parameter samples



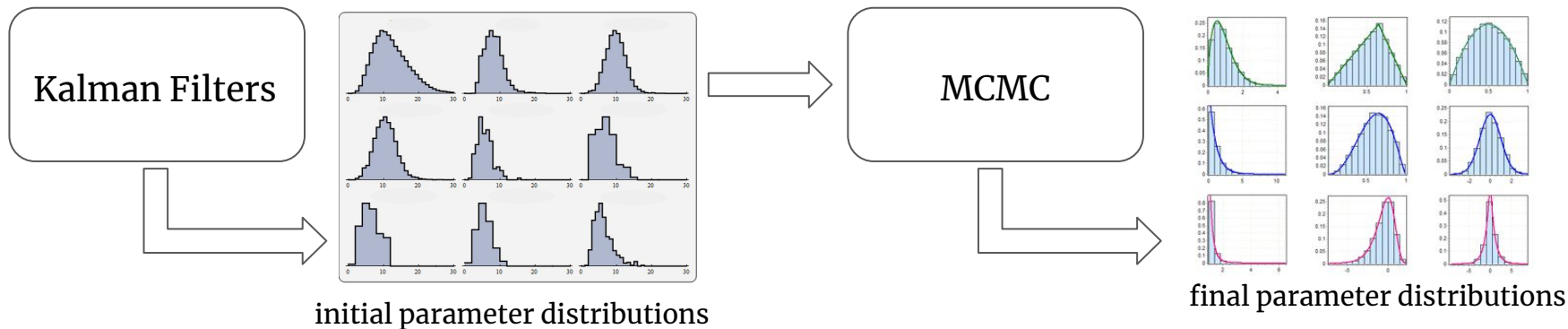
# Big Picture Diagram



# Combining the Methods

Goal: Use post-Kalman Filter output as pre-MCMC input

1. Use Kalman Filters to parameterize model
  - a. Fit distributions to output values
2. Use distributions as informative priors for MCMC
3. Parameterize with MCMC
4. Fit model



# Our progress

- Wrapping up
  - Early start (May)
  - Both teams successful in parameterizing T1D model
- Organization & Writing
  - Produce tutorial for parameterization using Predator-Prey (simpler model) as example
  - Clean and organize code for future use