# Bone Journal Club Math Modeling for Bone-Cell Dynamics

Horacio Gómez-Acevedo Department of Biomedical Informatics University of Arkansas for Medical Sciences

June 18, 2022

**UAMS** 

#### Overview

Math Modeling why?

Basic Ideas

Paper

Main Model

Ligands Competition

**Parameters** 

Simulations

Extensions of the Model

Osteoclast

Conclusions

What does it take to make the model?

What type of collaboration is necessary?

What type of experiments are required?

Is this the only type of model available?



#### Why?

- ▶ It is an attempt to introduce theoretical foundations to biological processes.
- It can also explain also some of the paradoxical observations.
- Based on "mechanistic" assumptions, models can produce useful predictions.
- Once a model is "calibrated", it can accommodate extensions based on new biological findings.

Basic Ideas

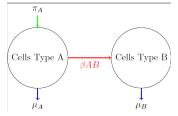
#### Compartmental Models

The so-called **Compartmental Models** try to describe the dynamics of cell interactions among two or more well-characterized cell types. Some basic implicit assumptions about cell populations

- ▶ The evolution of the population is described by rates (i.e., instant changes in population numbers).
- Cells are indistinguishable among the same type (A and B below).
- ► A and B represent abundance of the given type.

## ipartificitai Models (cont)

- Cells are entering (some progenitor cell) into the A compartment at a certain rate  $\pi_A$ .
- ► Cells leave the compartment (cell death) at the rate  $\mu_A$  and  $\mu_B$ , respectively.
- ▶ Cells evolve from Type A into Type B at a rate proportional to their abundance at a constant rate  $\beta$ .



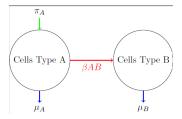
Basic Ideas

#### Compartmental Model Math

The translation of this interaction is translated in the following system of (ordinary) differential equations

$$A' = \pi_A - \beta AB - \mu_A A$$
  

$$B' = \beta AB - \mu_B B$$
(1)



Basic Ideas

#### "Solving" the equations

For the above system, we can calculate the "steady state(s)". This means the point(s) that the trajectories will end up reaching (after potentially some very long time) or they are getting away from.

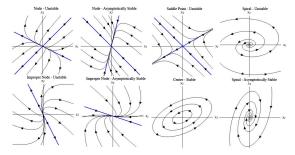


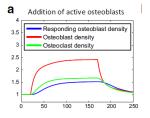
Figure: dynamical systems



## "Solving" the equations (cont)

In general, it is relatively hard to calculate those steady states and determine (locally) their behavior (attractor or repelor) (Mathematical issue)

Instead, we solve the equations "numerically". Meaning, we write code to simulated the trajectories (e.g., Matlab) for a given set of parameters ( $\pi_A$ ,  $\beta$ , etc.)





#### In Silico Simulations

A great deal of time is spent calculating the parameters from a given established system

- Using other literature sources
- Making simulations based on newly produced data

The ultimate goal is to produce a tuned *in silico* system based on equations that mimic fundamental biological concepts. Then, we can explore scenarios and test biological hypothesis.





## Today's paper

Bulletin of Mathematical Biology (2019) 81:3575–3622 https://doi.org/10.1007/s11538-018-0533-0



## SPECIAL ISSUE: MATHEMATICS TO SUPPORT DRUG DISCOVERY AND DEVELOPMENT



## Dynamics of Bone Cell Interactions and Differential Responses to PTH and Antibody-Based Therapies

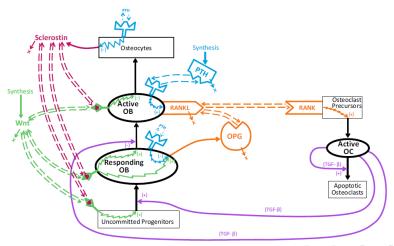
Vincent Lemaire<sup>1,2</sup> ○ · David R. Cox<sup>1</sup>

Received: 17 June 2017 / Accepted: 1 November 2018 / Published online: 20 November 2018 © Society for Mathematical Biology 2018



Main Model

#### Picture First



Main Model

## Cell Compartment Equations

$$R' = D_R \pi_C \pi_W - D_B \frac{\pi_W}{\pi_C} R$$

$$B' = D_B \frac{\pi_W}{\pi_C} R - \frac{k_e^B}{\pi_W} B$$

$$C' = D_C \pi_L - k_e^C \pi_C C$$
(2)

According to the model  $D_R$ ,  $D_B$  and  $D_C$  are constant differentiation rates,  $k_e^B$ , and  $k_e^C$  are constant elimination rates.

Ligands Competition

## Ligands Models

The modeling follows the enzymatic theory of Michaelis-Menten. In brief, if we have a substrate S reacting with an enzyme E to form a complex SE can be modeled as

Paper

$$S + E \underset{k_{-1}}{\overset{k_1}{\rightleftharpoons}} S \circ E$$

$$\frac{dS \circ E}{dt} = k_1 S \cdot E - k_{-1} S \circ E \tag{3}$$

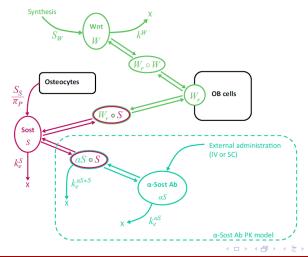
When the text refers that equations are considered at "steady state" it means that

$$k_1S \cdot E = k_{-1}S \circ E$$



Ligands Competition

## Ligand Models (cont)



## Binding to LPR5/6

The attachment of Wnt to the receptor  $W_r$  is taken at the steady state. The equations for binding of Wnt receptor and sclerostin are

$$\frac{dW_r \circ S}{dt} = k_9 S \cdot W_r - k_{10} W_r \circ S 
\frac{d\alpha S \circ S}{dt} = k_{13} S \cdot \alpha S - k_{14} \alpha S \circ S - k_e^{\alpha S \circ S} \alpha S \circ S$$
(4)

The second equation represents the presence of an antibody for Sost

#### Parameter Estimation

Table 2 These are the parameters of the bone model which were determined by optimization (fitting param-

eters)			
Symbol	Unit	Value	Description
$D_R$	pM/day	$1.28\times10^{-4}$	Differentiation rate of osteoblast progenitors into responding osteoblasts [see Eq. (1)]
$f_0$	None	$3.39 \times 10^{-2}$	Minimal TGF-β receptor occupancy [see Eq. (2)]
C <sub>50</sub>	pM	$1.25 \times 10^{-6}$	Osteoclast density to achieve half TGF- $\beta$ receptor occupancy [see Eq. (2)]
$D_B$	day <sup>-1</sup>	3.47	Differentiation rate of responding osteoblasts into active osteoblasts [see Eq. (1)]
$k_e^B$	day <sup>-1</sup>	$1.21 \times 10^{-3}$	Rate of elimination/death of active osteoblasts [see Eq. (1)]
$D_C$	pM/day	$7.12 \times 10^{-3}$	Differentiation rate of osteoclast progenitors into active osteoclasts [see Eq. (1)]
$k_e^C$	day-1	$6.46 \times 10^{-2}$	Rate of elimination/death of active osteoclasts [see Eq. (1)]
$K_D^O$	pM	$4.76 \times 10^{-6}$	Mixed parameter representing a typical density of OPG-producing cells [see Eq. (36)]
$K_{max}^{L}$	pmol/pmol of cells	4644.6	Maximum carrying capacity of cell-bound RANKL by osteoblasts [see Eq. (28)]
k3	$pM^{-1} day^{-1}$	0.368	RANK-RANKL association rate [Eq. (25)]
k4	day <sup>-1</sup>	65.64	RANK-RANKL dissociation rate [Eq. (25)]
$K_D^P$	None	20.17	Mixed parameter related to unbound PTH receptors in basal condition [see Eq. (24)]
K	pM	0.10	RANK density [see Eq. (26)]
$K_D^S$	None	14.95	Mixed parameter related to unbound sclerostin molecules in basal condition [see Eq. (19)]
$K_D^W$	None	3.70	Mixed parameter related to unbound Wnt molecules in basal condition [see Eq. (19)]

#### Journal Club Format

This is a new format for Journal Club

- ▶ We will explore more carefully the methodology.
- Most of the papers are going to require "heavy" tools from computer sciences, statistics and mathematics.
- It will be a transition time to understand each other (be patient)
- ► The dynamical nature of brain activity will make it very challenging to hold on to a single model.
- Complexity vs. Explainability is an implicit trade-off.
- ► The ultimate goal is to use and expand "acceptable" methodologies into new and more "appropriate" ones. Yes, this means **coding** (R, Python, MatLab).

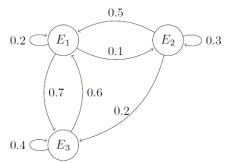


•0000000000

#### Hidden Markov Models

The implementation of Hidden Markov models dates back in the late 60's by Leonard Baum and collaborators. It is still an active area of research.

What is a Markov chain?

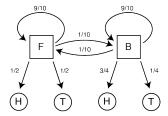




#### Hidden Markov Chains

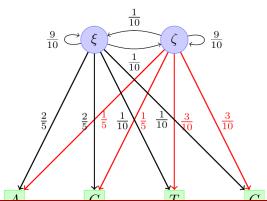
#### The fair casino problem

- You don't know if the dealer has a fair or unfair coin (Hidden states)
- You only observe the output (Emissions)



## Hidden Markov Chains (Genomics)

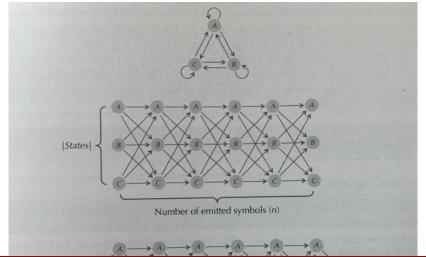
Another (unrealistic) example is to build a HMM to describe a (genetic) sequence





Is this the only type of model available?

## Viterbi's representation HMMs



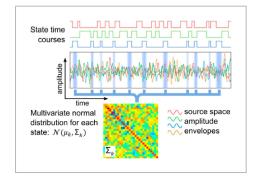
## Building a HMM

From Baker et al. 2014

Here, we present a study that identifies transient networks of brain activity, with no prior assumptions on the brain areas or time scales involved. This uses a distinct methodology based on a hidden Markov model (HMM), which infers a number of discrete brain states that recur at different points in time. Each inferred state corresponds to a unique pattern of whole-brain spontaneous activity, which is modeled by a multivariate normal distribution and a state time course indicating the points in time at which that state is active. These two outputs are shown schematically in Figure 1, and allow us to describe both the spatial and temporal characteristics of each inferred state.



## Building a HMM



**Figure 1**. Schematic of the HMM outputs. An HMM with K states is inferred from band-limited amplitude envelopes of source reconstructed MEG data. Each state is characterized by a multivariate normal distribution (defined by means  $\mu_k$  and covariance

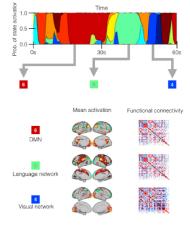


#### In the paper

The HMM is a family of models that can describe time series of data using a discrete number of states, all having the same probabilistic distributions but each having different distribution parameters. Thus, the states correspond to unique patterns of brain activity that recur in different parts of the time series. For each time point t, a state variable dictates the probability of each state being active at that moment

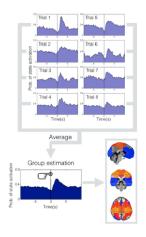
Is this the only type of model available?

#### General HMM at rest



Is this the only type of model available?

#### General HMM in task



#### General HMM cont

an HMM generally comprises the description of the states, the state time courses (which determines the probability of each state to be active at each time point in the time series) and the transition probabilities between the states (i.e. the probability to transition from each state to each other state). Because here we run the HMM on all concatenated subjects' datasets, the states and the transition probabilities are defined at the group level; the state time courses are however particular to each subject - that is, states can come active at different moments for each subject. Since the probability distribution of each part of the model depends on all others, there is no closed-form solution available