

Development and calibration of tumor models

Ernesto A. B. F. Lima
Emanuelle A. Paixão



MINISTÉRIO DA
CIÊNCIA, TECNOLOGIA
E INOVAÇÕES

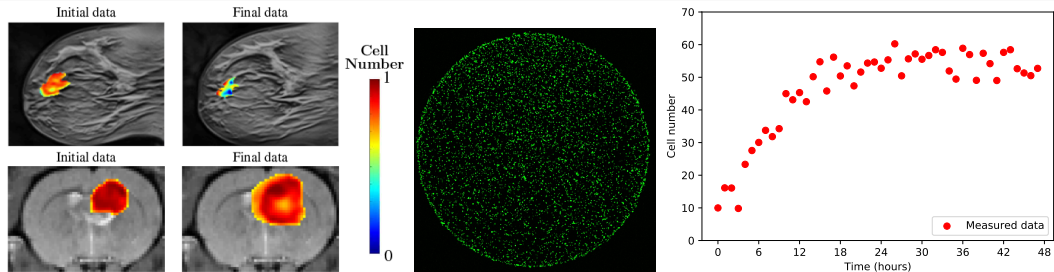


Model Calibration

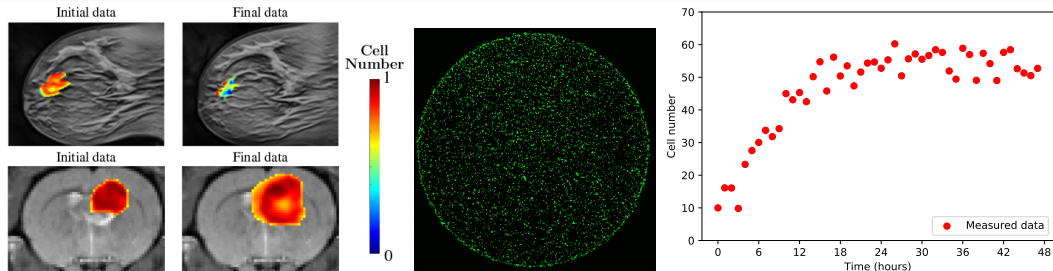
- Calibration Theory:
 - Maximum Likelihood Estimation
 - Bayesian Approach
- EMCEE Python Library¹

¹Foreman-Mackey, Daniel, et al. "emcee v3: A Python ensemble sampling toolkit for affine-invariant MCMC." arXiv preprint arXiv:1911.07688 (2019).

Motivation



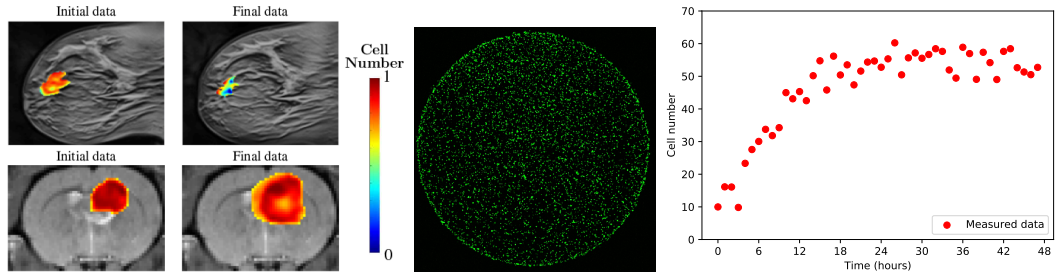
Motivation



$$\frac{dN}{dt} = rN \left(1 - \frac{N}{K} \right),$$

- N : number of tumor cells;
- r : tumor growth rate;
- K : environment carrying capacity.

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Model Calibration

It is done to **adjust** the selected model parameters, such as growth and death rates, to obtain the best fit between the **model** predicted responses and the available **data**.

Frequentist and maximum likelihood approaches

- there is an unknown but fixed parameter that represents the event;
- maximum likelihood approach: find the parameter that enables the model to deliver the best characterization of the true target distribution.

²Oden et al., Encyclopedia of Computational Mechanics Second Edition (2017)

Model calibration: frequentist and Bayesian statistics²

Frequentist and maximum likelihood approaches

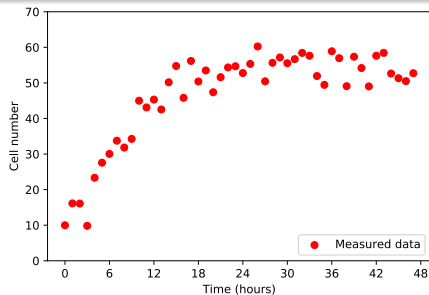
- there is an unknown but fixed parameter that represents the event;
- maximum likelihood approach: find the parameter that enables the model to deliver the best characterization of the true target distribution.

Bayesian approach

- it maps prior beliefs about the parameters to new posterior beliefs in the light of observing the data;
- the estimated parameter is regarded as a random variable, and the true parameter is merely a realization of the random variable.

²Oden et al., Encyclopedia of Computational Mechanics Second Edition (2017)

Definitions



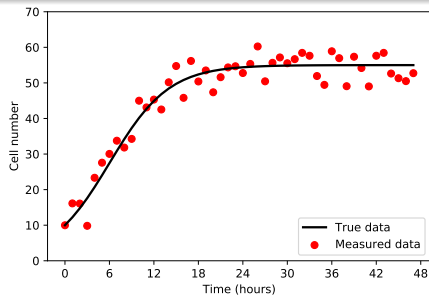
- D : measured data;

Mathematical model

$$\frac{dN}{dt} = rN \left(1 - \frac{N}{K} \right),$$

- θ : vector of model parameters, $\theta = (r, K)$;
- r : tumor growth rate;
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- $Y(\theta)$: model prediction;

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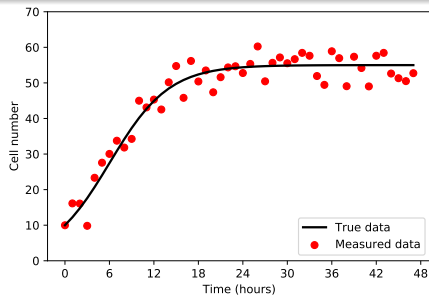
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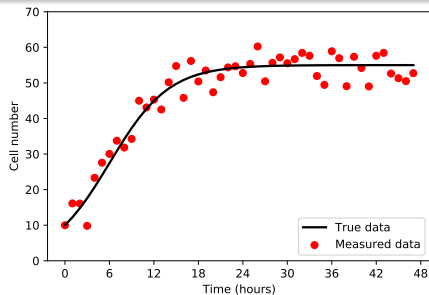
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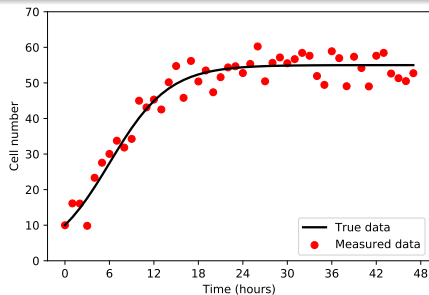
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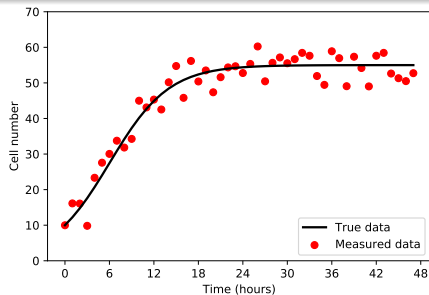
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Maximum likelihood estimation

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The conditional probability that the data (\mathbf{D}) is observed for a given set of parameters (θ) is the likelihood $\pi(\mathbf{D}|\theta)$.

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Assuming:

- 1 the experimental noise is normally distributed ($\epsilon \sim \mathcal{N}(0_{N \times 1}, \sigma_{data}^2 \mathbf{I}_{N \times N})$);
- 2 the model inadequacy is normally distributed ($\gamma \sim \mathcal{N}(0_{N \times 1}, \sigma_{model}^2 \mathbf{I}_{N \times N})$);
- 3 the variance of the total error (σ) is such as $\sigma^2 = \sigma_{data}^2 + \sigma_{model}^2$;
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$$\pi(\mathbf{D}|\boldsymbol{\theta}) = \prod_{i=1}^{N_t} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(D_i - Y_i(\boldsymbol{\theta}))^2}{2\sigma^2}},$$

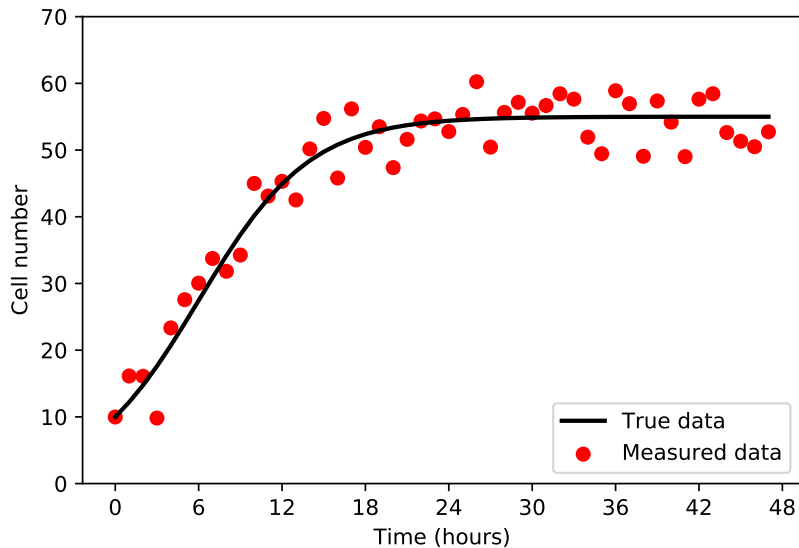
- N_t : the number of data points.

Find $\hat{\boldsymbol{\theta}} \in \Theta$, where Θ is the parameter space, that maximize the likelihood.

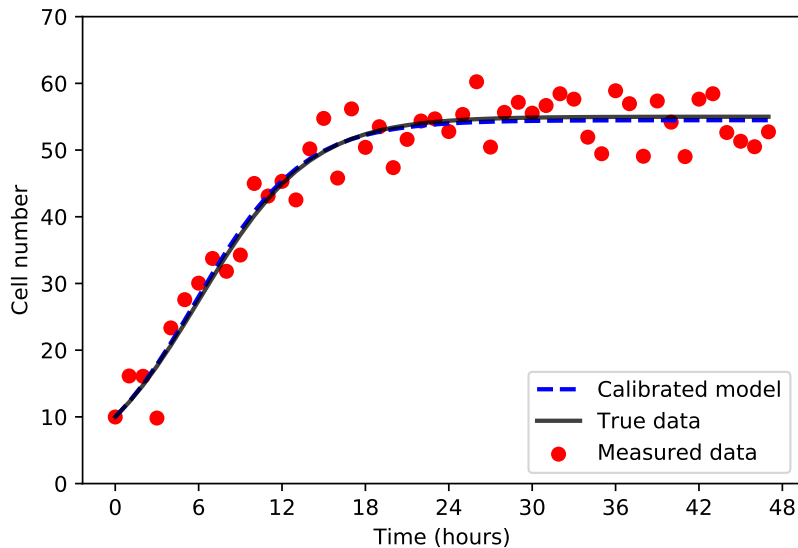
It is customary to work with the more manageable log-likelihood function.

$$\begin{aligned}\hat{\boldsymbol{\theta}} &= \underset{\boldsymbol{\theta} \in \Theta}{\operatorname{argmax}} [\log \pi(\mathbf{D}|\boldsymbol{\theta})]; \\ &= \underset{\boldsymbol{\theta} \in \Theta}{\operatorname{argmax}} \left[-\frac{1}{2} \sum_{i=1}^{N_t} \left(\log(2\pi\sigma^2) + \frac{(D_i - Y_i(\boldsymbol{\theta}))^2}{\sigma^2} \right) \right].\end{aligned}$$

Maximum likelihood estimation



Maximum likelihood estimation



$$\frac{dN}{dt} = rN \left(1 - \frac{N}{K} \right),$$

$$r = 0.25$$

$$K = 59.14$$

Bayesian approach

Given events A and B:

$$P(A, B) = P(A|B)P(B);$$

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Converting to probability densities π , if A represents the parameter θ of a model, and B the observational data \mathbf{D} :

$$\underbrace{\pi(\theta|\mathbf{D})}_{\text{posterior}} = \frac{\overbrace{\pi(\mathbf{D}|\theta)}^{\text{likelihood}} \overbrace{\pi(\theta)}^{\text{prior}}}{\underbrace{\pi(\mathbf{D})}_{\text{evidence}}};$$

$$\pi(\mathbf{D}) = \int_{\Theta} \pi(\mathbf{D}|\theta)\pi(\theta) d\theta$$

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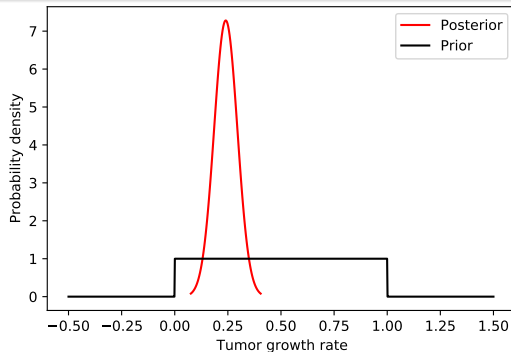
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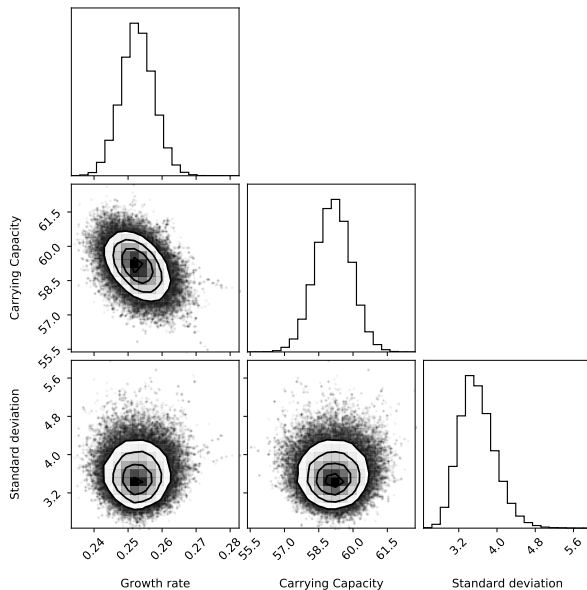


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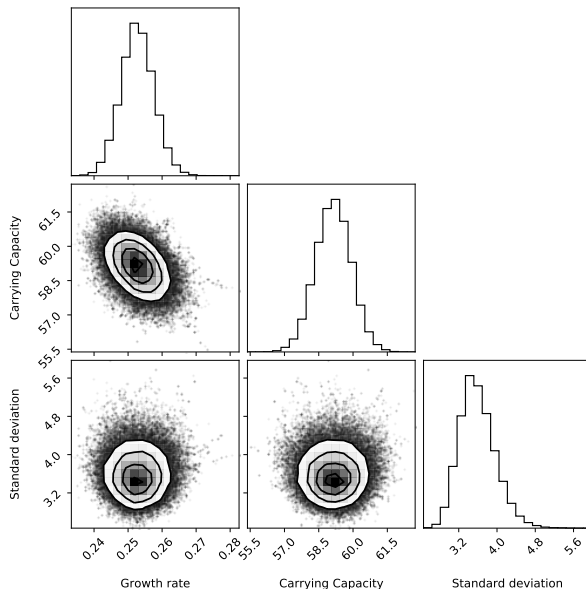
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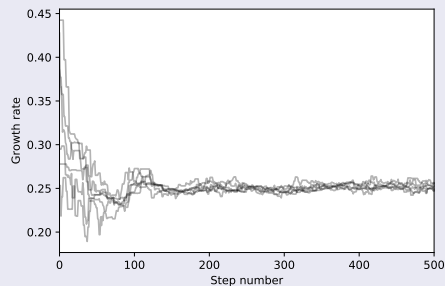


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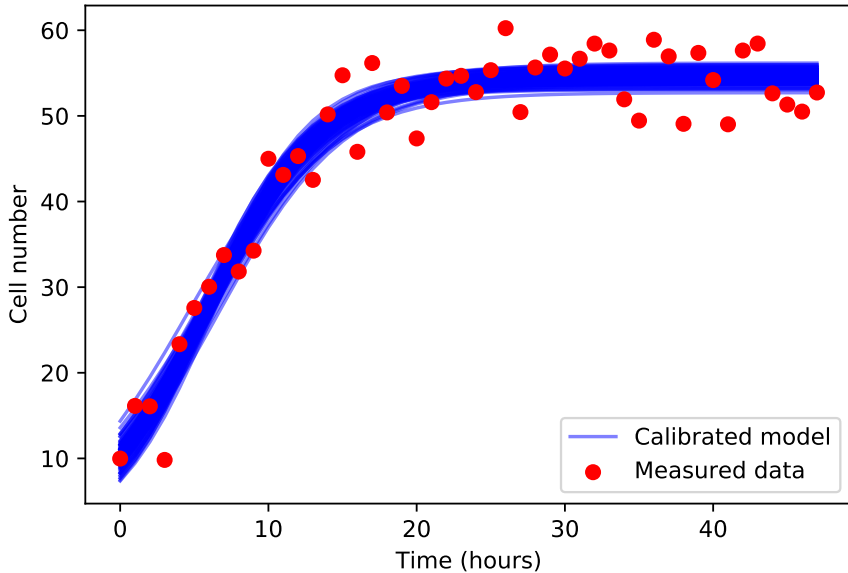


Markov Chain Monte Carlo:

Markov Chain Monte Carlo methods draw samples where the next sample is dependent on the existing sample, called a Markov Chain.



Bayesian approach



Jupyter Notebook - Binder and Discord

<https://github.com/ernesto-lima/veraolncc2021>

#mini-course-1 - Discord

EMMCCT 2021

#mini-course-1 MC01-CT: Development and Calibration of Tumor Models (Desenvolvimento e Calibração de Modelos Tumorais).

Uma aventura começa. Vamos adicionar alguns amigos!

Convidar pessoas

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- admin
- admin-messages
- Admin Voice Channel

PANELIST

- panelist-messages
- Panelist Voice Channel

EMMCCT 2021

- helpdesk
- announcements
- event-agenda
- posters
- mini-course-1
- mini-course-2
- random-talk

#

Bem-vindo(a) a #mini-course-1!

Este é o começo do canal #mini-course-1. MC01-CT: Development and Calibration of Tumor Models (Desenvolvimento e Calibração de Modelos Tumorais).

Editar canal

Anna Claudia Resende 22/01/2021

Professores:
Ernesto Lima (UT at Austin) e Emanuelle Arantes Paixão (LNCC).

Horários:
De quarta (27/01) a sexta (29/01) das 11:00h às 12:30h.

Os principais objetivos deste minicurso são:

- Familiarizar os participantes com a motivação biológica para o uso de diversos modelos de crescimento tumoral;
- Apresentar métodos de resolução de modelos de equações diferenciais ordinárias (EDO's), utilizando Python;
- Calibrar os modelos desenvolvidos via métodos Bayesianos.

Ementa:

- Desenvolvimento da parte teórica sobre modelagem em câncer (27/01): uma introdução sobre modelagem no contexto do câncer, abordando modelos discretos, contínuos e híbridos. Exemplificação e interpretação de diferentes tipos de funções para a descrição do crescimento tumoral, mortalidade, efeito Allee e terapias, entre outros fenômenos biológicos;
- Introdução à linguagem de programação Python (28/01): resolução de EDO's e diferentes tipos de função, trabalhadas durante o primeiro dia de curso, em Python;
- Desenvolvimento da parte teórica e prática sobre calibração (29/01): abordagem de conceitos relacionados à calibração, de forma mais específica à calibração Bayesiana. Os conteúdos teóricos e práticos serão abordados conjuntamente, por meio da calibração de um modelo de EDO, utilizando dados gerados. Nesta atividade, será trabalhada a resolução da EDO e construção de gráficos com os resultados obtidos, usando a biblioteca emcee para calibrar o modelo.

HELPDESK-2

- Anna Claudia Resende
- Emanuelle Paixão

ORGANIZER-2

- Luciana Barros
- Regina Almeida

PANELIST-1

- Heber Rocha

DISPONIVEL-7

- AlejandroHerrera
- eye5
- FelipeCandian
- LeoSouza
- Oscar Antezana
- Valerio
- VzMedivh

OFFLINE-52

- _lucasDC_
- AlejandroHerrera
- Alfredo Scari
- Allan Costa