

# Bayesian Inference Using Sequential Monte-Carlo Algorithm for Dynamic System Models

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July 27, 2020

MSc in High Performance Computing

The University of Edinburgh

Year of Presentation: 2020

## **Abstract**

This is the bit where you summarise what is in your thesis.

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## **Acknowledgements**

This template is a slightly modified version of the one developed by Prof. Charles Duncan for MSc students in the Dept. of Meteorology. His acknowledgement follows:

*This template has been produced with help from many former students who have shown different ways of doing things. Please make suggestions for further improvements.*

# Chapter 1

## Introduction

[background and motivation]

[what is done]



# Chapter 2

## Background

### 2.1 Zebrafish spinal cord regeneration

[describe the process and how cells and cytokines are involved]

### 2.2 Mathematical modelling

[how this can be modelled as dynamic systems]

[general topics of mathematical models: how to build model according to interactions; how to calibrate/ parameterise the model; how to solve the model; dynamics; how to evaluate the model]

### 2.3 Bayesian inference

[how to parameterise the model]

[how to infer the parameter given data]

[likelihood-free inference and information about ABC SMC]

[model comparison, ABC SMC for model comparison]

### 2.4 Software tools

[existing tools and software for this task]

[workflow and developing process]

# Chapter 3

## Mathematical modelling

Mathematical models can describe different kinds of dynamic systems, and thus can be used as a guide for prediction and analysis. An ideal model in our case, can represent reasonable interactions/effects between cells and cytokines and recover the observed data features in different time point.

Proposed models for the regeneration process are in the form of ordinary differential equations (ODE), specifically the time differential form. Terms in the ODE are mostly explainable and corresponds interaction paths.

### 3.1 Observed data

Our models is built on the basis of the existing experiments data form Tsarouchas et al.[1]. The measurement data include the number of three kinds of cells (neutrophil  $N$ , macrophage  $\Phi$  and microglia) and the relative concentration of four cytokines (il- $1\beta$ , tnf- $\alpha$ , tgf- $\beta 1a$  and tgf- $\beta 3$ ). As proposed in [1], neutrophil and macrophage play important roles in the promotion of spinal cord regeneration with il- $1\beta$  and tnf- $\alpha$  being the mediation. According to this, our current models focus on the changes of four variables  $N$ ,  $\Phi$ ,  $\beta$  (for il- $1\beta$ ) and  $\alpha$  (for tnf- $\alpha$ ).  $N$  and  $\Phi$  is of the unit ‘number of cells’,  $\beta$  and  $\alpha$  is of the unit ‘relative concentration’ (compared to the value at first time point).

It is noted that the variance of the measured data is relatively high. The summary statistic used for the parameter estimations is mean of measurement data at each time point, assuming that measured data is Gaussian-like distributed. To validate this, the distribution of the measured data points is plotted and examined to see if the mean value can represent the distribution. The result is that at most time points the measurement values are Gaussian-distributed, although some distributions are skewed. One abnormal distribution is observed at time point 120 h post-lesion (hpl) for macrophage where there are two concentrations. Mean value can summarise most data and thus is still used as the target observed data. A plot of the mean of the four variables is shown in Figure 3.1.

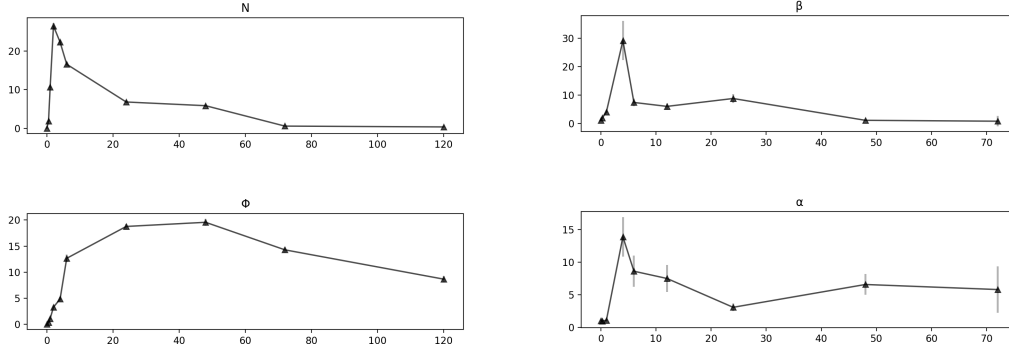


Figure 3.1: Mean of the observed data for neutrophil  $N$ , macrophage  $\Phi$ ,  $il-1\beta$  and  $tnf-\alpha$ , from experiment results of [1]. Error bars indicate standard error of mean

## 3.2 Hypothesis and Models

5 models in total are proposed according to different hypothesis. At first our tests and implementations of ABC SMC for parameter estimations use only the basic model for developing propose. After the parameter estimation framework is built and tested, more models are proposed, in order to calibrate and adjust the basic model such that it can represent the observed regeneration process better or can be used to test our hypothesis.

All these models assume the involved interactions is within two kinds of cells (neutrophil and macrophage) and two kinds of cytokines ( $il-1\beta$  and  $tnf-\alpha$ ) and use the data presented in Figure 3.1 for the inference task. Interactions or effects from other cells or cytokines is not considered as there might not be corresponding data available.

### 3.2.1 Basic model

A preliminary model is proposed according to [1] and used to build and test the inference framework code. An interaction map of the model is shown in Figure 3.2. This model is a simplification a the process described in [1] with some minor interactions ignored. To describe the parameters' units, we denote the unit of  $N$  and  $\Phi$  i.e. number of cells as 'cell', and denote the unit of  $\beta$  and  $\alpha$  i.e. relative mRNA expression as 'unit' for simplicity.

It is assumed that there are negative feedbacks for all the variables. MORE DESCRIBE.



Figure 3.2: Interactions modelled in the basic model (model 1) based on Tsarouchas et al.[1]. Lines ended with arrow represent promoting effect, lines ended with T-connectors represent inhibition

$$\begin{aligned}
 \frac{dN}{dt} &= \lambda_N + \kappa_{N\beta}\beta - \mu_N N - \nu_{N\Phi} N \Phi \\
 \frac{d\Phi}{dt} &= \lambda_\Phi + \kappa_{\Phi\beta}\beta - \mu_\Phi \Phi \\
 \frac{d\beta}{dt} &= \frac{s_{\beta N} N}{1 + i_{\beta\Phi} \Phi} - \mu_\beta \beta \\
 \frac{d\alpha}{dt} &= s_{\alpha\Phi} \Phi - \mu_\alpha \alpha
 \end{aligned} \tag{3.1}$$

Parameter	Definition	Units
$\lambda_N$	Self-increase rate of neutrophil	$cell/h$
$\kappa_{N\beta}$	Promoting effect coefficient by $il-1\beta$	$cell/(unit \cdot h)$
$\mu_N$	Coefficient of negative feedback of $N$	$h^{-1}$
$\nu_{N\Phi}$	Coefficient of inhibition of both $N$ and $\Phi$	$cell^{-1} \cdot h^{-1}$
$\lambda_\Phi$	Self-increase rate of macrophage	$cell/h$
$\kappa_{\Phi\beta}$	Promoting effect coefficient by $il-1\beta$	$cell/(unit \cdot h)$
$\mu_\Phi$	Coefficient of negative feedback of $\Phi$	$h^{-1}$
$s_{\beta N}$	Production rate from $N$	$unit/(cell \cdot h)$
$i_{\beta\Phi}$	Coefficient of inhibition to the production	$cell^{-1}$
$\mu_\beta$	Coefficient of negative feedback of $\beta$	$h^{-1}$
$s_{\alpha\Phi}$	Production rate from $\Phi$	$unit/(cell \cdot h)$
$\mu_\alpha$	Coefficient of negative feedback of $\alpha$	$h^{-1}$

Table 3.1: Parameters introduced in the basic model (model 1)

### 3.2.2 Alternative models

**Model 2 and model 3** As the observed data indicate, this dynamic system has a steady state where the inflammation is resolved and immune cells should not be present at the injury site. Regarding this, the self-increase parameter  $\lambda$  cannot be constant, thus a exponentially decaying  $\lambda$  term is introduced and model 2 is proposed. (Eqn. 3.2). Also, the inhibition of il-1 $\beta$  production, i.e. term  $i_{\beta\Phi}\Phi$  is considered to be ignored for a more simple model, in which case the relative expression of il-1 $\beta$  is only affected by the number of neutrophil and the negative feedback from itself. This case corresponds to model 3, written as Eqn. 3.3.

Model 2 and model 3 introduce one extra parameter  $a$ , which is a coefficient in the exponentially decaying  $\lambda$ , determining the decay speed, with the unit  $h^{-1}$ .

$$\begin{aligned}\frac{dN}{dt} &= \lambda_N e^{-at} + \kappa_{N\beta}\beta - \mu_N N - \nu_{N\Phi} N \Phi \\ \frac{d\Phi}{dt} &= \kappa_{\Phi\beta}\beta - \mu_{\Phi}\Phi \\ \frac{d\beta}{dt} &= \frac{s_{\beta N} N}{1 + i_{\beta\Phi}\Phi} - \mu_{\beta}\beta \\ \frac{d\alpha}{dt} &= s_{\alpha\Phi}\Phi - \mu_{\alpha}\alpha\end{aligned}\tag{3.2}$$

$$\begin{aligned}\frac{dN}{dt} &= \lambda_N e^{-at} + \kappa_{N\beta}\beta - \mu_N N - \nu_{N\Phi} N \Phi \\ \frac{d\Phi}{dt} &= \kappa_{\Phi\beta}\beta - \mu_{\Phi}\Phi \\ \frac{d\beta}{dt} &= s_{\beta N} N - \mu_{\beta}\beta \\ \frac{d\alpha}{dt} &= s_{\alpha\Phi}\Phi - \mu_{\alpha}\alpha\end{aligned}\tag{3.3}$$

Model 3 can be regarded as a simplification of model 2, as it can be treated as model 2 with parameter  $i_{\beta\Phi} = 0$ . Among the proposed three models, model 1 is a naive one that was proposed at very first time and used as an ODE ‘template’ to build and test parameter inference framework. As the implementation was successful, model 2 and 3 was proposed as we were trying to calibrate some terms and find a better model. After fitting, model 2 is supposed to be better than model 1 as it corrects the problem that appears at the final time points (which relate to the steady state). Model 3 makes a small simplification on model 2 and is theoretically less ‘general’ than model 2.

**Model 4 and model 5** After the first model selection experiment, it was found that some significant features presented in the observed data were not recovered by any

of the existing model. To resolve this, attempts were tried to introduce more interactions within the dynamic system considering the biological and mathematical context. Extra promoting effect to the expression of  $\text{tnf-}\alpha$  was considered, by either adding a phenomenological term (which means the same effect as directly promoting but the underlying mechanism is unclear) or adding a term that represents a promoting effect to the production process of  $\text{tnf-}\alpha$ , namely model 4 (Eqn. 3.4) and model 5 (Eqn. 3.5).

$$\begin{aligned}
\frac{dN}{dt} &= \lambda_N e^{-at} + \kappa_{N\beta}\beta - \mu_N N - \nu_{N\Phi} N \Phi \\
\frac{d\Phi}{dt} &= \kappa_{\Phi\beta}\beta - \mu_{\Phi}\Phi \\
\frac{d\beta}{dt} &= s_{\beta N} N - \mu_{\beta}\beta \\
\frac{d\alpha}{dt} &= s_{\alpha\Phi}\Phi - \mu_{\alpha}\alpha + d_{\beta\alpha}\beta
\end{aligned} \tag{3.4}$$

$$\begin{aligned}
\frac{dN}{dt} &= \lambda_N e^{-at} + \kappa_{N\beta}\beta - \mu_N N - \nu_{N\Phi} N \Phi \\
\frac{d\Phi}{dt} &= \kappa_{\Phi\beta}\beta - \mu_{\Phi}\Phi \\
\frac{d\beta}{dt} &= s_{\beta N} N - \mu_{\beta}\beta \\
\frac{d\alpha}{dt} &= (s_{\alpha\Phi} + f_{\beta\alpha}\beta)\Phi - \mu_{\alpha}\alpha
\end{aligned} \tag{3.5}$$

Parameter	Definition	Units
$d_{\beta\alpha}$	Coefficient of promoting effect from $\beta$	$h^{-1}$
$f_{\beta\alpha}$	Coefficient of promoting the production of $\alpha$ by $\beta$	$cell^{-1} \cdot h^{-1}$

Table 3.2: Parameters introduced in model 4 and 5

### 3.2.3 Model evaluation and comparison

[general topics on evaluating a model]

[bayes factor for model selection]

### 3.2.4 Limitations

[hypothesis]

[available data]

[model misspecification]

# Chapter 4

## Parameter estimation and model comparison

Estimation of parameters in the proposed models is the main task of this section, which involves the implementation of ABC SMC and several experiments. ABC SMC-based model selection is another task that can be easily conducted with the developed parameter inference framework.

The build and test of code were under `Python` environment with `pyABC`[2]. Some other code e.g. shell script and `R` code are also used to perform the experiments and analyse the results. Software and system environment used in our implementation can be found at Appendix A. The build and test were performed on local computers and HPC facilities available within EPCC.

### 4.1 Implementations and code

[ABC implementations details, e.g. distance, population, ODE related functions]

[how the code is developed and built]

According to our preliminary studies, ABC SMC framework implemented using `pyABC` in `Python` was adopted in this project. `pyABC` is a popular SMC software packages [2] that has been used form many SMC studies and applications [8]. `pyABC` provides an open-source framework for likelihood-free inference, which is an implementation of ABC SMC algorithm and a tool-box for our own inference and analysis tasks. Besides, it supports multi-core execution implemented using `multiprocessing` package for scaling-up, which is of our interests and suitable for the followed performance experiments.

The inference framework code for the project was developed and tested in local environment (macOS 10.15.6, see Table A.1) at first, then the functional version was deployed on compute node of ARCHER and Cirrus for parameter inference experiments

and model selection task. The scaling-up experiment was performed on Cirrus, and the profiling and its analysis were performed on local machine. Some development and debug were on the remote machines to ensure experiments run correctly on compute node.

The ODE model-related code and utilities were firstly developed to enable reusable functions, variables and data calls. It includes the code for the ODE models, ODE solver, data structures, data format transform functions etc. By doing this in a separate code file, we can change options and activate ABC SMC easily in the implementation code file, without creating definition and duplicated code for the models and parameter priors.

Some modifications were made to the source code of `pyABC`. For example, the laboratorial measured data were not considered ‘complete’ for modeling and analysis purpose: the available time points for cells and cytokines are different, e.g. cell number was not measured at 0.25 hpl and cytokines’ expression was not measured at time point 120 hpl. These missing values were treated as ‘ignored’ when calculating the distance between observed data and simulated data. To cope with this built-in distance function code is modified.

Analysis code was also wrapped up into functions which can be easily called after an ABC SMC run is finished, which includes multiple visualisations and summary statistic of the results. For different tasks there are also separated analysis code file. Other analysis tools used in the project include built-in database visualisation tool, R code and Microsoft Excel.

The project code was managed via `git` version-control and available as a GitHub repository<sup>1</sup>; it also made the cross-hardware synchronisation of code versions convenient.

After several development iterations, code files for ABC SMC implementation now mainly had two types: code files for infer-back experiments (using synthetic data), and code files for parameter inference (using experimental data). Model selection can be easily done by adding more model to the implementation code file.

## 4.2 ABC SMC and model hyperparameters experiments

As the key focus of this project is on the parameter estimations of dynamical system, the ability of inference on the proposed models was firstly examined before actual inference using the experimental observed data.

In the first part, synthetic data is used with known true parameter values. The algorithm implementation is evaluated by the efficiency and goodness of resultant model under different implementation options and ABC SMC hyperparameters.

---

<sup>1</sup>[https://github.com/chaolinhan/MSc\\_Project](https://github.com/chaolinhan/MSc_Project)



Then according to findings in the first part, several options with good performance are tried in the inference using experimental observed data (Figure 3.1). To obtain a more accurate and general results, these experiments are repeated for 3 or more times.

[including the options that are tested/ tried/ not adopted]

[including experiments results and discussions]

[how do these options correspond to biological model and how to set them accordingly for proposed model]

The ABC SMC inference can have largely different performance when using different hyperparameters and implementation options. To firstly test the ability of inference and observe the results of different options, synthetic data with known true parameter values are used as target data. The true value of parameters that are used to generate synthetic data is listed in Appendix B.1. These true values are firstly obtained by fitting a least square fit of model 1 onto the experimental data (Figure 4.1), the target data is then generated using these parameter values via ODE solver in `Python`.

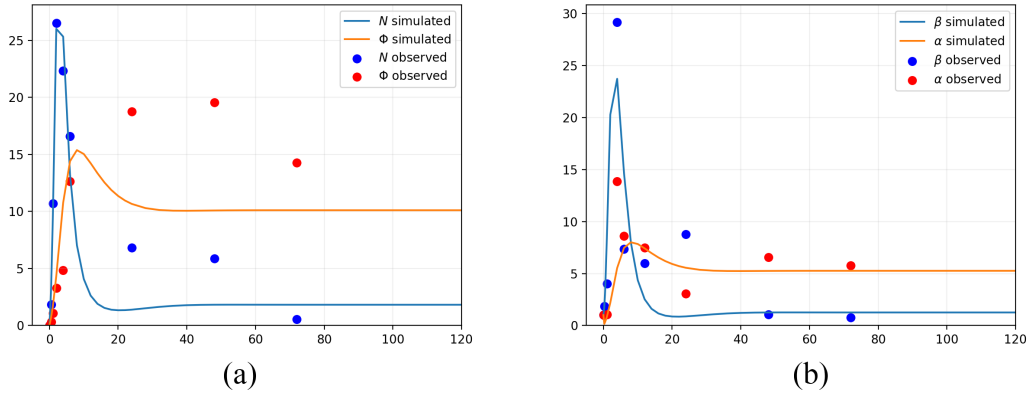


Figure 4.1: Synthetic data generated with known parameter values (line plot), compared to experimental data (scatter plot)

Among them the following topics are studied using synthetic data.

#### 4.2.1 Perturbation kernels

Perturbation kernels work in the sampling process. In each generation  $t$ , samples are firstly taken from the previous population  $\{\theta_{t-1}\}$  with weights  $\{w_{t-1}\}$ , then perturbed using the perturbation kernel  $K(\theta|\theta^*)$ . We keep sampling until  $N$  particles are accepted, where  $N$  is the pre-set population size. After that the new weights are calculated and normalised.

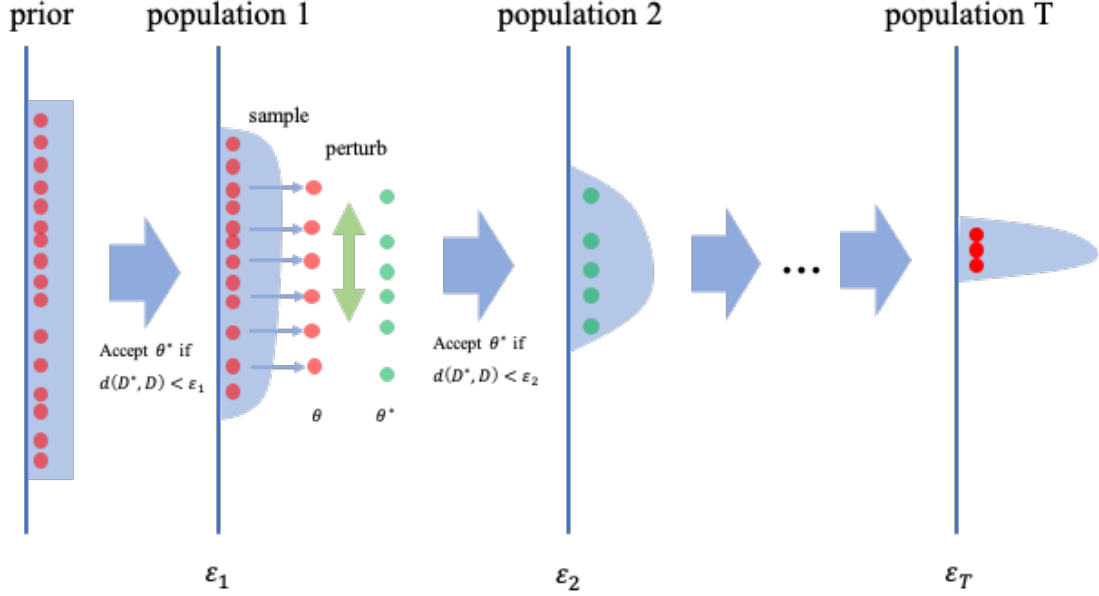


Figure 4.2: ABC SMC sampling process

The perturbation kernel is called in the sampling of every particles and determines how the new perturbed particle is chosen, thus it is influential to both computation complexity and the resultant posterior distribution. Generally, a local perturbation kernel may face the risk of being stuck in local modes (e.g., local optimal), but it may need less computational operations, or could generate a population with a higher acceptance rate if the successive epsilon values are close; A kernel with wide variance, or spreading out in a large space could help in resolving the local optimal problem by a more thoroughly exploration of the parameter space, however it can be more computation-intensive and result in a lower acceptance rate. A desired optimal kernel should balance the trade-offs; their property and criteria is discussed in [3].

There are several common choice of perturbation kernels. Among them multivariate normal kernel and local M-nearest neighbour model is preferred to be applied on our models. A covariance matrix  $\Sigma_t$  of accepted particles is calculated from previous generation and used in multivariate normal kernel:  $K(\theta|\theta_{t-1}) \sim \mathcal{N}(\theta_{t-1}, \Sigma_t)$ . It is illustrated to be more efficient than uniform kernel and component-wise normal kernel in relecting the true posterior structure [3]. It has been proved to perform well in several dynamic system models [4, 5, 6] for the parameter estimation and model selection tasks. The *scaling*  $\in (0, 1]$  parameter in `pyABC` will be multiplied to the covariance to produce a ‘narrower distributed’ perturbation result.

Local M-NN kernel provided by `pyABC` is also tried to provide a comparison. A local kernel density estimation (KDE) fit is used with M nearest neighbours considered.

The kernel experiments is designed to explore the efficiency of SMC on our dynamical systems. Given the same fixed threshold schedule, kernels that need less total samples

and have higher acceptance rate would be our preference. The experiments compared multivariate normal kernel with local MNN kernels with different parameters, using synthetic data to infer back the parameters. The acceptance rate among each time point and total required samples are compared after the experiment to give suggestions on the kernel selection in the real data inference. As the threshold schedule is fixed, the final population should have similar discrepancy to the target data thus here the goodness of fit i.e. recover of target data trends/features and errors of the inferred parameters compared to true values is not discussed.

### Kernel experiment results

To compare kernels, a fixed schedule is used with minimal epsilon i.e.  $\epsilon_t$  set to 10.0. From the total required samples graph Figure 4.3, the efficiency can be compared. Among the tested kernels, the local M-NN with  $M=50$  has the best performance: it requires the least number of samples and has higher acceptance rates among almost all generations. Local M-NN with  $M=750$  is the slowest kernel.

For local M-NN kernels, generally a greater  $M$  will lead to lower acceptance rate and more required particles in each generation. As shown in Figure 4.4, local M-NN with  $M=750$  is the lowest curve. Consequently, if greater  $M$  is test, then it will have even lower acceptance rates; the maximum  $M=2000$  (whole population is considered) will have the lowest acceptance rates.

Multivariate normal kernel has a performance between local M-NN  $M=250$  and  $M=100$ . It proves that rather than a trivial normal kernel, multivariate normal kernels is more efficient facing the concentrations of joint distributions among multiple parameters [3]. ‘Scaling’ option can narrower the distribution calculated from the last population, thus making the kernel more ‘local’ by sampling under a smaller variance. Similar to small  $M$  in local M-NN, small ‘scaling’ is also more efficient in our experiment of the model 1. Besides the fixed threshold schedule, a median threshold schedule with the same final threshold  $\epsilon_{20} = 10.0$  is also tested and similar results are observed (Figure B.1 and B.2, Appendix B2).

It seems that a more ‘local’ kernel can give better performance by efficiently sampling around concentrations in parameters’ distribution and approximate the posterior distribution. This holds in most cases under a given target final threshold value  $\epsilon_t$ , however may not produce the proper result want: a more local kernel, e.g. local M-NN with small  $M$  and multivariate normal with ‘scaling’ is more likely to be stuck in local optimality, as the kernel is less likely to sample particles that are far from local concentrations, although these local optimal are still accepted under given threshold. In other words, using local kernels the epsilon may quickly converge to local optimal; if a even smaller epsilon is desired, the local kernel can hardly generate enough particles to find another matched local modes. Also, the shapes of posterior distribution will affect the performance of local kernels [3]. One obvious example is presented in Figure 4.3, where local M-NN with  $M=50$  suffered from a local optimal: the last generation takes

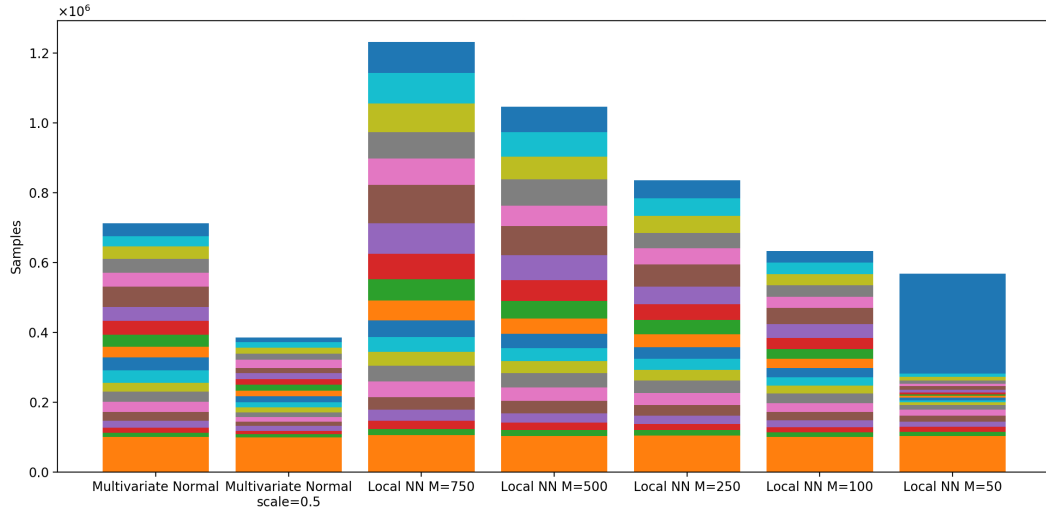


Figure 4.3: Total required samples of different kernels. Different color represents different generations (bottom to top: generation 1 to generation 20)

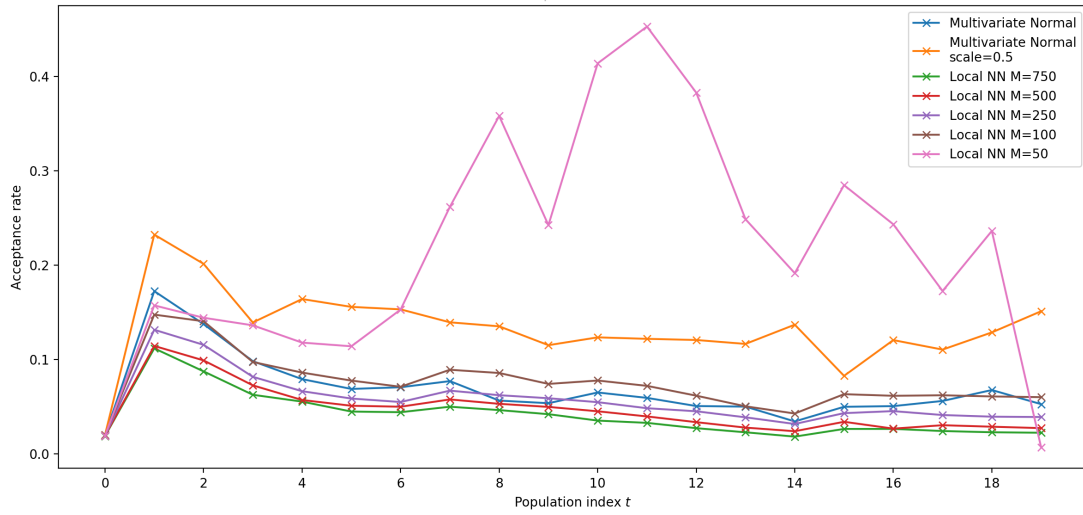


Figure 4.4: Acceptance rates of different kernels

much more samples to meet the required threshold.

## Conclusion

Local kernels can be fast but unstable in some case; for a general parameter inference of our models, multivariate kernels are preferred, as a good fit is our prior target; some local kernels are also worth trying after the multivariate normal kernel, e.g. local M-NN with  $M \leq 250$  (for population size of 2000, i.e. 12.5% of the population) and multivariate normal with scaling. Also multivariate M-NN is worth trying, although it is not built in `pyABC` and requires additional implementations.

### 4.2.2 Adaptive functions and factors

[how adaptive distance work]

SMC can be more adaptive by introducing adaptive distance function and adaptive population; besides, factors can be applied to manually ‘normalise’ the data.

The trivial distance function is set to Euclidean distance (2-norm distance)

$$D = \sqrt{\sum_i \Delta x_i^2} \quad (4.1)$$

where  $i$  is the index of data points and  $\Delta x_i$  is the discrepancy between observed data and simulated data at data point  $i$ , i.e.  $\Delta x_i = x_{i,simulated} - x_{i,observed}$ . In this case data points are 12 time points of four variables i.e. 48 data points in total.

A weighted 2-norm distance can be written as

$$D = \sqrt{\sum_i w_i \Delta x_i^2} \quad (4.2)$$

where a weight  $w_i$  is assigned to every data point. If data point  $i$  have a higher weight, then the data value is regarded to be more informative, i.e. giving more help in inferring the true posteriors; weights can be either pre-set according to prior knowledge of the problem, or using adaptive method to be dynamically calculated according to , known as adaptive distance.

Adaptive distance is changing the weights of all data points after each generation iteration, trying to assign informative data points higher weights. Additionally, implementation of adaptive in `pyABC` also introduces additional factors  $f_i$  multiplied to weights [7]

$$D = \sqrt{\sum_i f_i w_i \Delta x_i^2} \quad (4.3)$$

Factor is helpful as an option for efficiency. When some data points are equally informative, the manually pre-defined can make the distance more focused on certain data point, or behave like a normalisation that can balance the scales of different summarised statistics (here is the 48 mean values). There are two appliance case studied: (1) factors used as an normalisation option and (2) factors used to give more focus on some features of the observed data. For (2), as we noticed that the main features (e.g. rapid increase, peaks, fluctuations) are mostly observed in the first half of the time points i.e. 0 - 30 hpl, factors are tried in the later parameter estimation of real data where a more accurate fit of the curve is desired.

Adaptive population [8] can adapt the population size of each generation according to the mean correlation of variation error of the previous population. In our early test the maximal population size that is allowed is set to 5,000 and the adaptive strategy always select the upper bound, as a results of wide parameter space or the wide posterior approximation shape.

[what is factor]

[what is adaptive distance]

## Experiments results

[FIGURE here]

Two types of factors and adaptive distance function are tested by running the same number of generations (20 generation, 2000 particles per generation). From FIGURE, by applying factors the total required samples are less, and the adaptive distance requires much less samples; their acceptance rates are also higher than the standard one. It seems that adaptive function and factors could help to converge more quickly.

However considering the result after 20 generation (FIGURE), the resultant model gives the contrary preference. Applying factors and using adaptive distance can lead the resultant model less accurate (after the same generation iterations): they have wider inter-quantile range and may requires more generations to converge.

## Conclusion

We noticed the significant efficiency improvement of these adaptive options; they can largely improve the acceptance rate in some cases. However, as the factors and weights are directly multiplied to  $\Delta x$  and thus the metrics for distance are changed, a direct

compare of the efficiency under the same threshold schedule is unfeasible; after the same number of generations they can reach a small  $\epsilon_t$  but still the approximated posterior is not as accurate as the standard implementation. AS a result, our implementation of the parameter inference will only consider standard distance function and factors are only tested for improvements (FIGURE).

### 4.2.3 Data size, prior distribution and population

[experiments plan]

Some other hyperparameters, e.g. feed-in data size, prior distribution, number of populations and number of particles in each population were also of our interest. Experiments were designed to explore how these options affect the goodness of fit and efficiency of the implementation.

Regarding the dynamic systems model, SMC was applied with two data size options, three prior distribution (uniform distribution, wider uniform distribution and log-uniform distribution). The population options i.e. population size and number of populations were also tried with different values. These experiments intended to give suggestions on the later SMC implementation on experimental data.

### Experiments results

The results from data size and prior distribution range is shown in FIGURE. The standard implementation is fed with 120 data points (30 data points for each of the four variables), the ‘less data’ is fed with 48 data points, which is the case of the real experimental measurement. Although much less (60%) data is used, the total required sampling numbers is not much less (XX%). Although the data size does not affect the sampling process much and the inferred model are all considered acceptable when compared to the synthetic data (FIGURE), cares should be taken when using less data point, or using other more summative statistics, e.g. mean, standard deviation, peak values, starting and ending values etc. As shown in [6], less data can lead to a model with more variance, under-fitting or missing some local features e.g. local peak.

The prior range and distribution can largely affect the execution of SMC (FIGURE and FIGURE). Samples are taken from a high dimensional parameter space in each sampling process, wider prior distribution ranges will making each sampling explore more in the parameter vector space. It suggests that a narrower prior is preferred and we should make a more accurate and confident prior belief as possible for the efficiency concerns.

[discuss uniform and log uniform when result ready]

[FIGURE HERE]

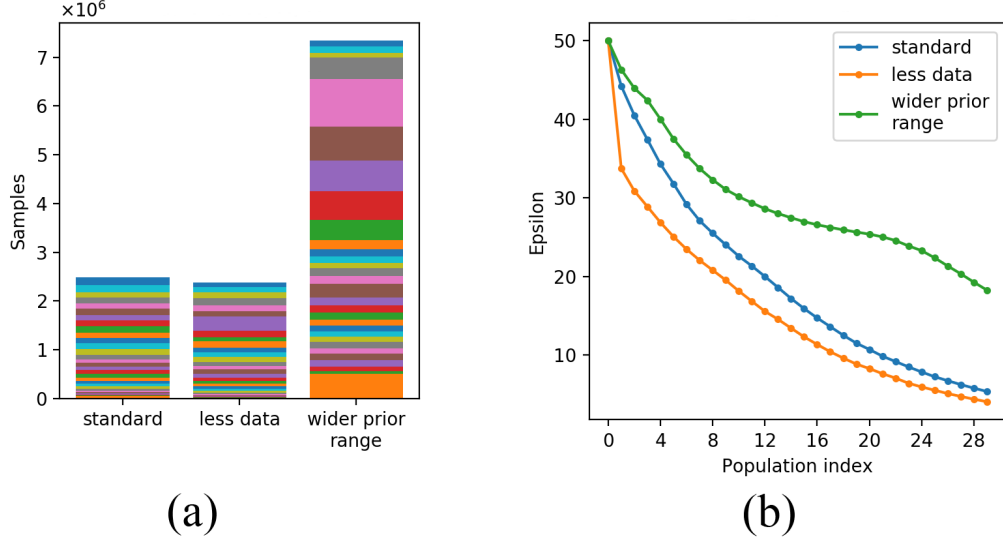


Figure 4.5: Data size and prior distribution range experiment. (a) Total required samples, (b) Epsilon values under median epsilon schedule

### Summary

This subsection aims to preliminarily explore ABC SMC settings using synthetic data with known true parameter values, thus the efficiency and the goodness of the resultant model can be compared across these options. Conclusion can be drawn to choose efficient and proper options of ABC SMC to be applied on the target models with experimental data. It also provides reference for a general inference task using SMC with high dimensional parameter space.

## 4.3 Parameter estimation and model comparison

### 4.3.1 Model 1, 2 and 3

[separated ABC run on model 1, 2 and 3]

Using the suggested options in the previous section, the target data (Figure 3.1) is prepared as input for the SMC inference framework. Regarding the result, the population size and number of generations are adjusted several times to obtain an general informative posterior which should be stable across repeated runs and avoid local optimal as much as possible.

Parameter estimation of model 1, 2 and 3 was tried with different prior distribution setting: distribution range  $[0, 25]$  and  $[0, 75]$ , and distribution type uniform and log-



uniform. All these ABC SMC runs uses 2,000 particles per population and 30 generations.

Log-uniform-shaped prior seems to give a better fit of the model, and wider prior range [0, 75] does not give a more accurate result. Then distribution range [0, 25] was tried, in case some parameter have a true posterior laying between [25, 50].

The results of prior distribution log-uniform [0, 50] is shown in Figure 4.6. For model 3, the acceptance rates and epsilon path are presented in Figure 4.7. For model 3, the estimated parameters' posterior is shown in Figure 4.8. Figure 4.6 plots the estimated curve of models, using the mean value of each parameter's approximated posterior; also 1000 particles (each particle is a parameter set) were sampled and used to generate simulated trajectories of the four variable, and the mean (blue) and 25th to 75th percentile range (grey) are calculated from the 1000 simulated data.

Before applying model comparison methods, some features of the three model can still be compared. From simulated curves, It can be seen that all the inter-quartile ranges are tight around the mean value curve, which indicates the approximated posterior are concentrated to some degree; the peak-shaped posterior distributions (Figure 4.8) agrees with this. All epsilon values converges to a steady level, and model 3 has a lower final epsilon value and consequently the simulated trajectory is more close to the observed data (model 3, Figure 4.6).

The acceptance rates is fluctuating and have a gradually increase trend for all the three models, as the acceptance rate becomes higher when the true posteriors are gradually approximated. Compared to model 1, model 2 gives a better fit of the decreasing trend at the second half of the observed data, by using a exponentially decaying self-increase rate  $\lambda_N$  instead of a constant. The resultant simulated data from model 2 and 3 are in the similar trends and the most obvious difference is that for model 3, the simulated data of  $\Phi$  and  $\alpha$  are more 'flat'. We expect model 3 to be the best model as it reaches a threshold value and intuitively gives a better fit, although the fit could not be considered generally a good representation of the biological process that we want to model, as the simulated data are significantly biased from the observed data for  $\text{tnf-}\alpha$ . A sharp peak at 4 hpl is observed from the measurement (Figure 3.1) but no similar features are represented by any of the three models.

[model comparison among model 1, 2, 3]

Next a model selection experiment with different prior was conducted, using the same ABC-SMC framework. As in the parameter inference, two distributions (uniform and log-uniform) are tested with three different interval ([0, 25], [0, 50] and [0, 75]). The results show that model 3 wins with nearly 100% model probability at most runs after 30 generations, except log-uniform [0, 75]. All the model probability results are of great discrepancy (e.g. 100% model 3 and 0% for model 1 and 2), so Bayesian factor is not calculated.

Figure 4.9 shows the model selection process, under log-uniform [0, 50] prior distribution. Model 3 gains total advantage over model 1 and 2 after 7th population. Together

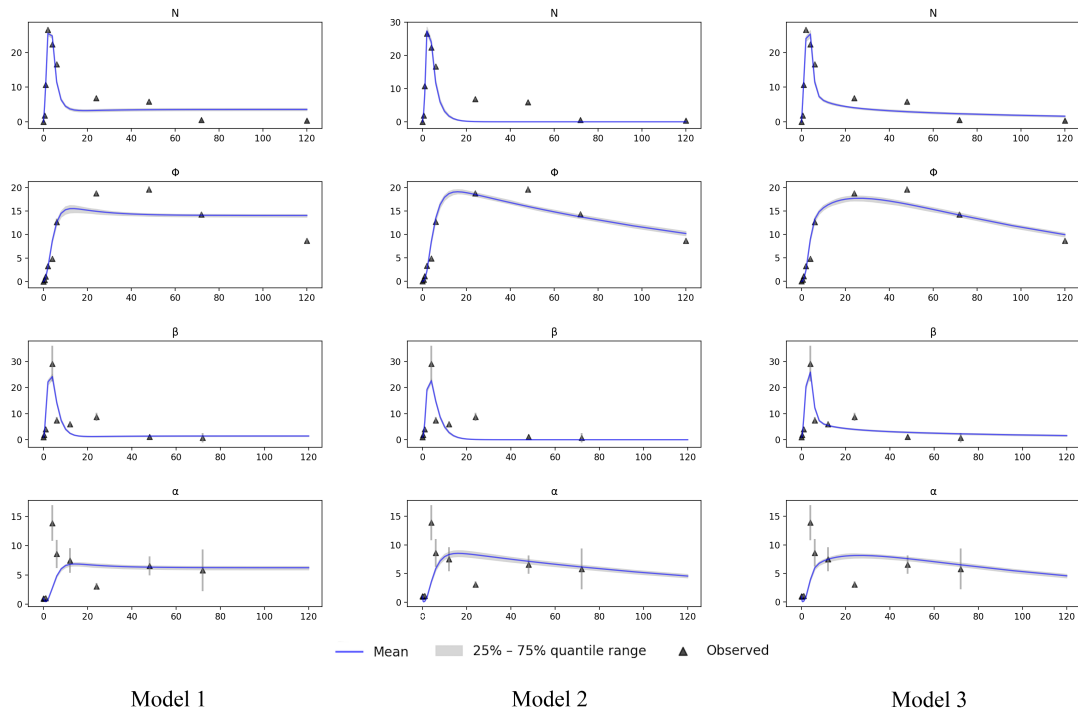


Figure 4.6: Simulated trajectory from the last population of model 1, 2 and 3

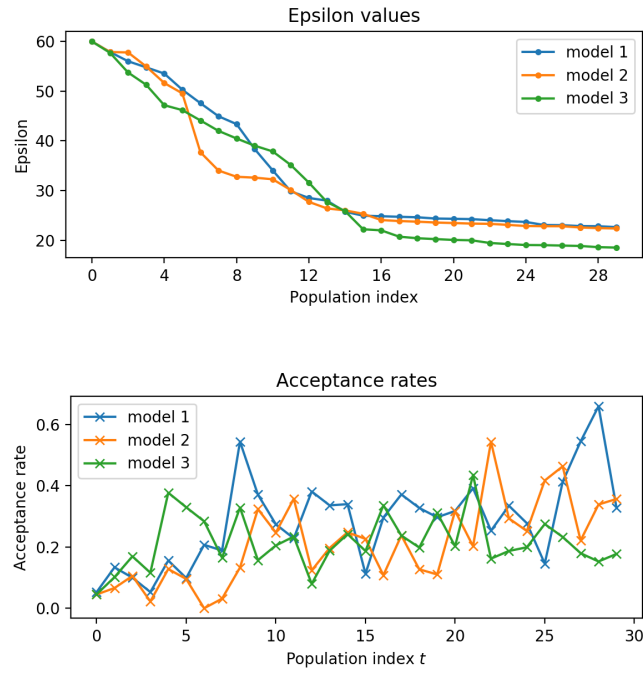


Figure 4.7: Epsilon trends and acceptance rates of model 1, 2 and 3

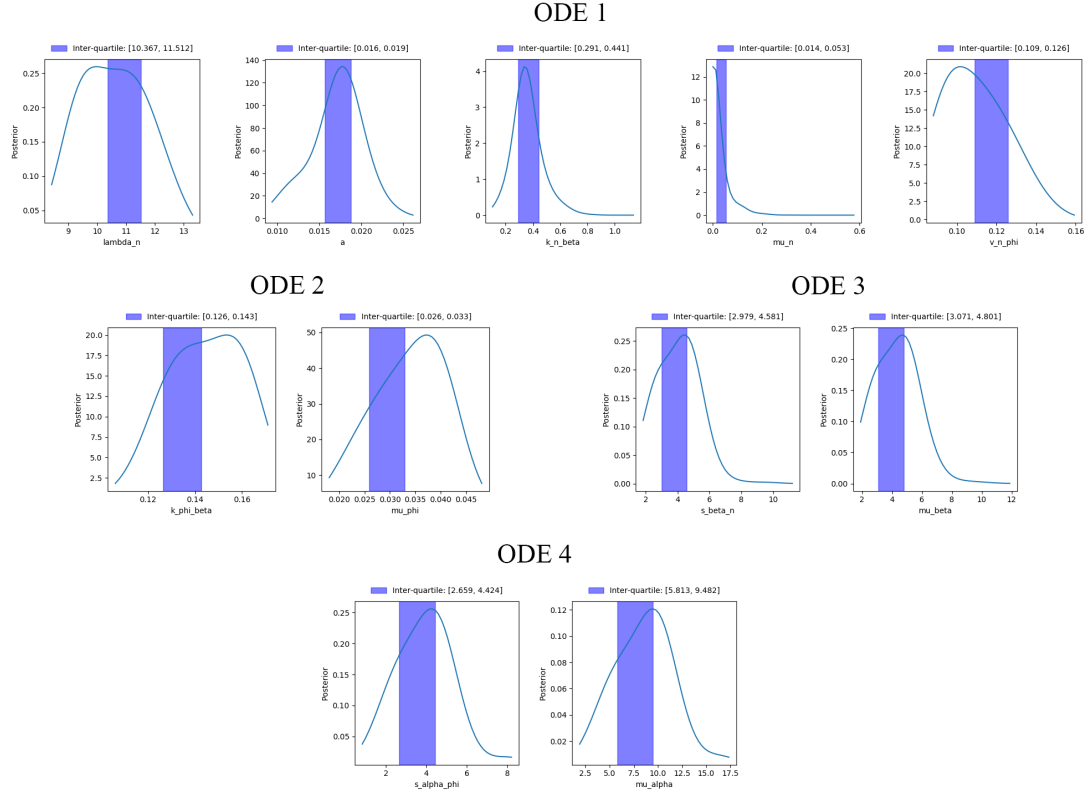


Figure 4.8: Estimated posterior distribution of parameters in model 3

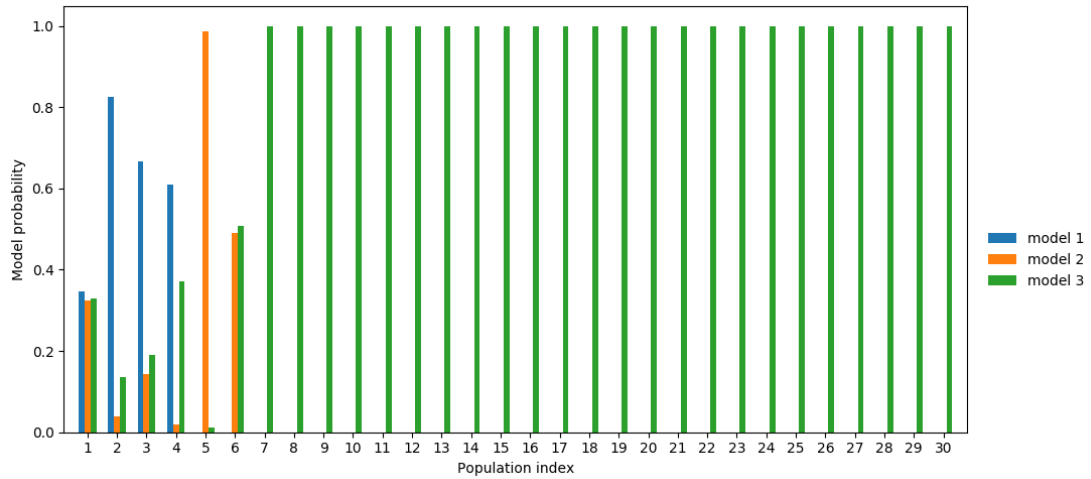


Figure 4.9: Model comparison of model 1, 2 and 3

Parameter	Estimated mean value (uniform)	Estimated mean value (log-uniform)
$\lambda_N$	14.156	13.296
$a$	9.670	0.017
$\kappa_{N\beta}$	18.001	0.259
$\mu_N$	13.196	0.018
$\nu_{N\Phi}$	0.742	0.131
$\kappa_{\Phi\beta}$	0.239	0.156
$\mu_{\Phi}$	0.154	0.035
$s_{\beta N}$	6.752	1.213
$\mu_{\beta}$	6.378	1.315
$s_{\alpha\Phi}$	16.997	5.826
$\mu_{\alpha}$	11.859	2.434

Table 4.1: Estimated parameter values of model 3

with conclusions above, model 3 is considered to be the the best model to represent the target data so far.

Compared to uniform distributed prior, we found that log-uniform distributed prior is more suitable in the inference. Log-uniform results in an obviously better fit and narrower inter-quantile interval (Figure 4.6 and B.3), and the final epsilon value is also smaller. Log-uniform tends to assign values that are close to the left boundary (i.e. zero in our case) higher density, i.e. they are more likely to be sampled in the first population. As a result, the estimated parameter posteriors are expected to have smaller mean and/or skewed to left of the x-axis. The estimated values proved this (see 4.1; also observed in other models and prior interval experiments). It indicates that some of the true parameter tend to have small values that are close to zero, and using log-uniform distribution could results in a faster and more satisfying inference. Regarding this, further experiments all use log-uniform distribution only.

### 4.3.2 Model 4 and 5

[features that derive model 4 and 5]

We observed that the existing models cannot well represent the trajectory of relative expression of  $\text{tnf-}\alpha$ : from experimental data, a rapid increase of  $\text{tnf-}\alpha$  expression is observed in 0–4 hpl, followed by a rapid drop; all the models cannot well recover this feature and most test results see a less-rapid increase followed by a gradually decrease and the observed peak value is not reached (e.g. Figure 4.6). Also in some other case e.g. Figure B.3,  $\text{tnf-}\alpha$  trajectories is well fitted at the cost of under-fitting  $\Phi$ . Hence efforts had been spent to propose more alternative models that can possibly solve this problem.

The two proposed alternative models is based on model 3 and try to add extra term in

the  $\text{tnf-}\alpha$  equation  $d\alpha/dt$ . As macrophage is the main source of  $\text{tnf-}\alpha$  production, and a similar sharp increase-and-drop trend is observed in the  $\text{il-1}\beta$  trajectory, two hypothesis and corresponding terms are propose as follows.

**Model 4** It is assumed that the expression of  $\text{il-1}\beta$  would have a promoting effect, representing by a phenomenological term  $d_{\beta\alpha}\beta$  and  $d_{\beta\alpha}$  is a new model parameter (positive constant). The promoting effect here is regarded to have the equivalent effect as directly promoting by  $\text{il-1}\beta$ , but the underlying mechanism is unclear so far. In mathematical view, this additional term can accelerate the expression of  $\text{tnf-}\alpha$  in the first few time points and help to recover the peak-shaped trajectory. The proposed model is written as Equation 3.4.

**Model 5** Alternatively, we considered promotions to the  $\text{tnf-}\alpha$  production, i.e.  $s_{\alpha\Phi}\Phi$ . It is assumed that  $\text{il-}\beta$  could accelerate the production process. An additional term  $f_{\beta\alpha}\beta$  is introduced to production rate, with  $f_{\beta\alpha}$  being a new model parameter (positive constant). This model meets the biological context considering the source of  $\text{tnf-}\alpha$ . The proposed model is written as Equation 3.5.

[further comparison of model 3, 4 and 5]

Model 4 and 5 are base on model 3, so in this phase experiments of these three models are conducted for separately parameter inference and overall model comparison. Based on our experience in conducted experiments, we used the following setting for parameter inference:

- population size: 2000 and 5000
- number of populations: 30 generations
- prior:  $[0, 50]$  log-uniform
- perturbation kernel: multivariate normal kernel

Factors (Equation 4.3) are also tried to find if we can force the inference framework to give more importance on the first few data points. All these runs are conducted on remote machines and the output database files are retrieved form analysis.

Figure 4.10 shows the simulated data from the inferred models, with population size 2000. It can be seen that

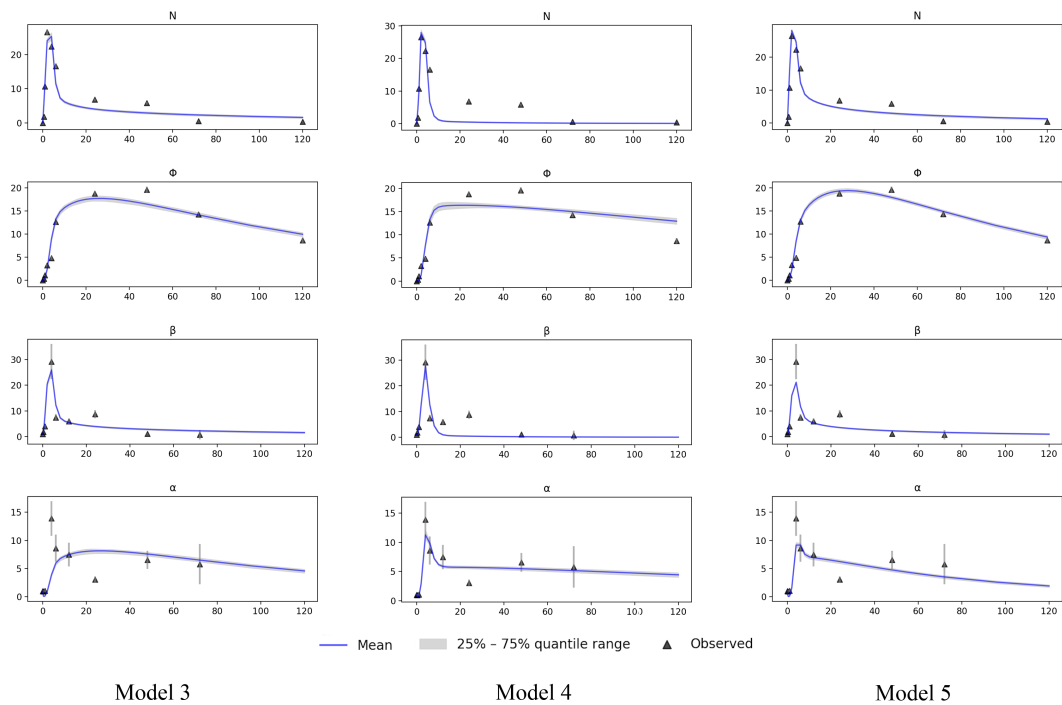


Figure 4.10: Simulated data from the last population of model 3, 4 and 5

# Chapter 5

## Performance experiments

The performance experiments are designed to explore the parallel performance of ABC SMC implementations. Usually ABC SMC is a time-consuming and computation intensive task and usually is executed on large clusters. The scheduling strategy, implementation details and many other factors can affect the parallel efficiency.

[MORE meanings of the performance study]

### 5.1 Scaling-up

First experiments are designed to illustrate the scaling-up performance. The program used here is an implementation of ABc SMC on model 5. The details of the ABC SMC settings is listed below

- Prior distribution: default to log-uniform distribution  $[1 \times 10^{-6}, 50]$  for all the 12 parameters
- threshold schedule: median epsilon
- No factors, no adaptive distance or adaptive population applied
- Population size is 2000, with 20 generations

[HOW PYABC parallelise the sampling]

For HPC systems like Cirrus, `pyabc` uses `multiprocessing` for multi-core parallel sampling. By default if the number of cores is not specified, it will automatically read the number of available cores and use them all. Cirrus has a 36-core CPU which support hyperthreading, such that the maximal number of cores available to `multiprocessing` is 72.

The program is executed on Cirrus, using 8, 12, 16, 24, 36, 54 and 72 cores respectively. Each run is repeated 5 times. The average execution time, required sampling numbers

are recorded. Hyperthreading is enabled when using 54 and 72 cores. The access to the node that contains computation cores is exclusive, such that the execution would not be affected by other programs or operations.

The implementation of ABC SMC in `pyabc` enables the parallelisation of sampling, which is the most time-consuming part. The rest part of the program is mostly not parallelised, e.g. database I/O and reductions operations. The sampling process involves sampling, perturbation and test of the acceptance criteria, all of which are computation-intensive.

In practice, using ABC SMC to estimate the parameters of a given model could cost up to several hundred of hours if the computational resources are limited[REF]. The performance experiment result could provide a reference that illustrates how the efficiency changes when scaling-up or the trade-offs in computational resources' cost and their benefit.

## Results

[scaling-up performance: speed-up and efficiency]

## 5.2 Profiling

The performance could also be analysed given a profiling report. The second experiment profiles the program to reveal the detailed time consumption for each operation and the possible bottleneck, according to which we could find the hot-spot of program and give possible suggestions on improving the performance.

In this case, profile tools `cProfile` and `yappi` are used in PyCharm IDE.

## Results

[profiling results: hot-spot and possible improvements]



# Chapter 6

## Future works

[something not done as scheduled]

[interesting topics to look inside]

[moving to generalisations]

# Chapter 7

## Conclusions

[what is studied]

[to what extend]

[how good is the result]

[summary of the findings and advise]

[thanks]

# Appendix A

## System and software environment

### A.1 ABC SMC implementation

#### A.1.1 Local machine

Local development machine is a Mac laptop, running on macOS 10.15.6. The environment of the development is listed in Table A.1.

Environment	Version
$\lambda_N$	2.1989
$\kappa_{N\beta}$	3.9627
$\mu_N$	1.7219
$\nu_{N\Phi}$ 0.2195	$cell^{-1} \cdot h^{-1}$
$\lambda_\Phi$	1.3146 $cell/h$
$\kappa_{\Phi\beta}$ 0.1235	$cell/(unit \cdot h)$
$\mu_\Phi$ 0.1454	$h^{-1}$
$s_{\beta N}$	6.5536 $unit/(cell \cdot h)$
$i_{\beta\Phi}$ 1.7062	$cell^{-1}$
$\mu_\beta$	0.5212 $h^{-1}$
$s_{\alpha\Phi}$ 10.2416	$unit/(cell \cdot h)$
$\mu_\alpha$ 19.6642	$h^{-1}$

Table A.1: Environment on local machine

#### A.1.2 Remote machine

### A.2 Data analysis

Environment	Version
$\lambda_N$	2.1989
$\kappa_{N\beta}$	3.9627
$\mu_N$	1.7219
$\nu_{N\Phi}$ 0.2195	$cell^{-1} \cdot h^{-1}$
$\lambda_\Phi$	1.3146 $cell/h$
$\kappa_{\Phi\beta}$ 0.1235	$cell/(unit \cdot h)$
$\mu_\Phi$ 0.1454	$h^{-1}$
$s_{\beta N}$	6.5536 $unit/(cell \cdot h)$
$i_{\beta\Phi}$ 1.7062	$cell^{-1}$
$\mu_\beta$	0.5212 $h^{-1}$
$s_{\alpha\Phi}$ 10.2416	$unit/(cell \cdot h)$
$\mu_\alpha$ 19.6642	$h^{-1}$

Table A.2: Environment on remote machine

# Appendix B

## Data and settings

### B.1 Infer-back experiments

#### B.1.1 Parameter values used to generate synthetic data

Parameter	Value	Unit
$\lambda_N$	2.1989	$cell/h$
$\kappa_{N\beta}$	3.9627	$cell/(unit \cdot h)$
$\mu_N$	1.7219	$h^{-1}$
$\nu_{N\Phi}$	0.2195	$cell^{-1} \cdot h^{-1}$
$\lambda_\Phi$	1.3146	$cell/h$
$\kappa_{\Phi\beta}$	0.1235	$cell/(unit \cdot h)$
$\mu_\Phi$	0.1454	$h^{-1}$
$s_{\beta N}$	6.5536	$unit/(cell \cdot h)$
$i_{\beta\Phi}$	1.7062	$cell^{-1}$
$\mu_\beta$	0.5212	$h^{-1}$
$s_{\alpha\Phi}$	10.2416	$unit/(cell \cdot h)$
$\mu_\alpha$	19.6642	$h^{-1}$

Table B.1: Parameter values used for model 1

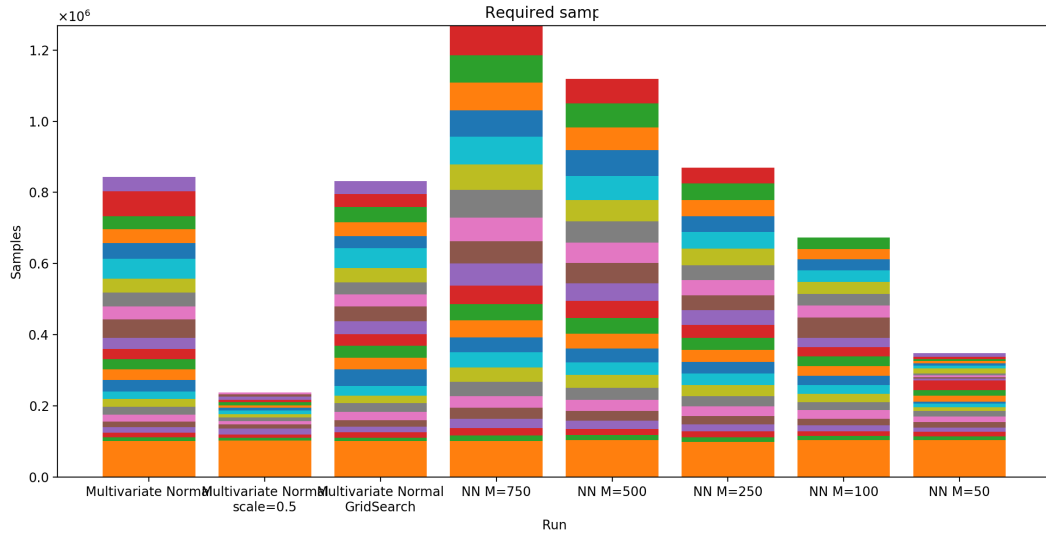


Figure B.1: Total sampling size

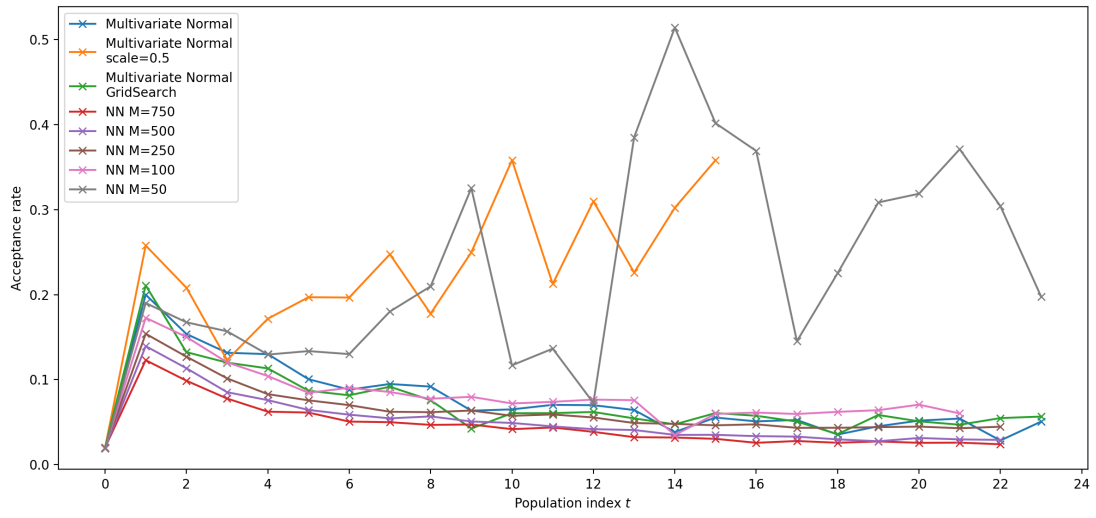


Figure B.2: Acceptance rates

### B.1.2 Kernel experiment: median epsilon schedule

## B.2 Parameter inference and model comparison results

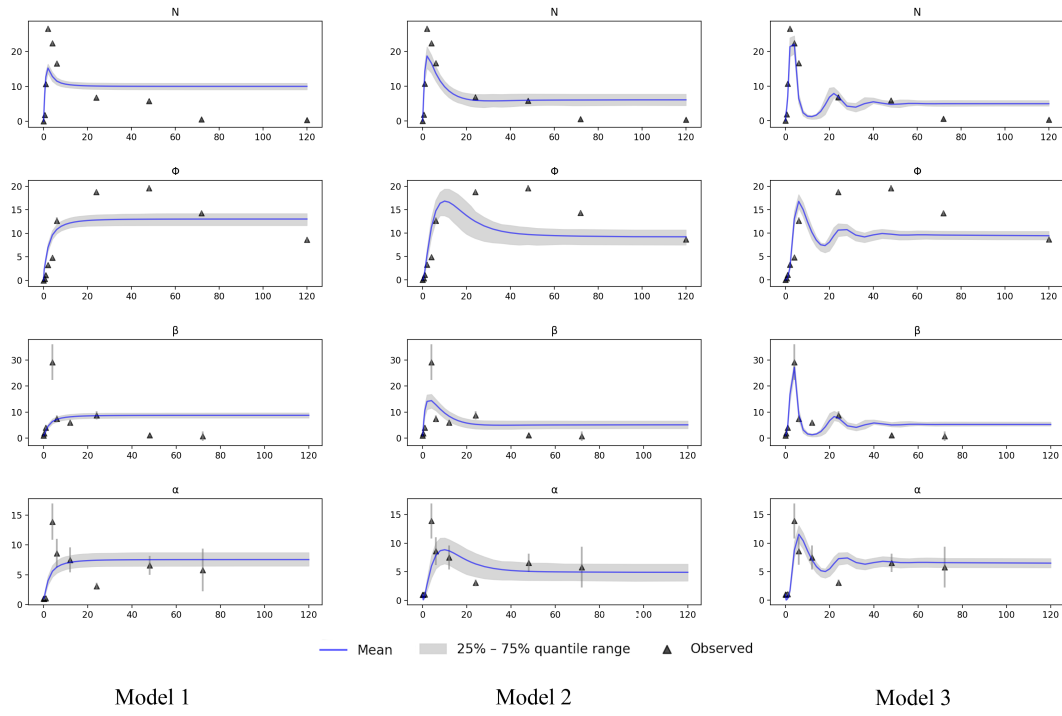


Figure B.3: Total sampling size

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