# Fitzhugh-Nagumo Bayesian Parameter Estimation Benchmarks

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```
using DiffEqBayes, BenchmarkTools
using OrdinaryDiffEq, RecursiveArrayTools, Distributions, ParameterizedFunctions,
CmdStan, DynamicHMC
using Plots
gr(fmt=:png)
Plots.GRBackend()
```

#### 0.0.1 Defining the problem.

The FitzHugh-Nagumo model is a simplified version of Hodgkin-Huxley model and is used to describe an excitable system (e.g. neuron).

```
fitz = @ode_def FitzhughNagumo begin
  dv = v - v^3/3 - w + 1
  dw = \tau inv*(v + a - b*w)
end a b \tauinv l
(::Main.##WeaveSandBox#312.FitzhughNagumo{Main.##WeaveSandBox#312.var"###Pa
rameterizedDiffEqFunction#332", Main.##WeaveSandBox#312.var"###Parameterized
TGradFunction#333", Main. ##WeaveSandBox#312.var"###ParameterizedJacobianFunc
tion#334", Nothing, Nothing, Modeling Toolkit. ODESystem )) (generic function wit
h 1 method)
prob_ode_fitzhughnagumo = ODEProblem(fitz,[1.0,1.0],(0.0,10.0),[0.7,0.8,1/12.5,0.5])
sol = solve(prob_ode_fitzhughnagumo, Tsit5())
retcode: Success
Interpolation: specialized 4th order "free" interpolation
t: 14-element Array{Float64,1}:
 0.0
 0.15079562872319327
  0.6663735500745417
  1.4549121831880751
  2.6341751496828474
  3.7872864628874394
  5.149282290423124
  6.764810407399299
  7.606020974182365
```

```
8.324334146165869
  9.040772814596577
  9.552575705603262
 9.985208121599765
10.0
u: 14-element Array{Array{Float64,1},1}:
 [1.0, 1.0]
 [1.0242787914016627, 1.0109527801835287]
 [1.0925382825360388, 1.0495725586393927]
 [1.147894455050522, 1.1102123746508352]
 [1.134543873591793, 1.1975474781177977]
 [1.0432761941043434, 1.2718688798460578]
 [0.8446920007269357, 1.3381007267503957]
 [0.3135440377028956, 1.3689380033842313]
 [-0.4098348685955019, 1.342759540998098]
 [-1.4082544459528368, 1.2706202503513042]
 [-1.909783303000839, 1.1563318788556225]
 [-1.9618464536295719, 1.0688710996087507]
 \hbox{\tt [-1.9544223037206336, 0.9966722929830949]}
 [-1.9538629866249133, 0.9942458205399927]
Data is genereated by adding noise to the solution obtained above.
t = collect(range(1,stop=10,length=10))
data = convert(Array, VectorOfArray([(sol(t[i]) + sig*randn(2)) for i in 1:length(t)]))
2\times10 Array{Float64,2}:
1.18958 1.31193 1.14998 1.12624 ... -0.738646 -1.89938 -2.1636
```

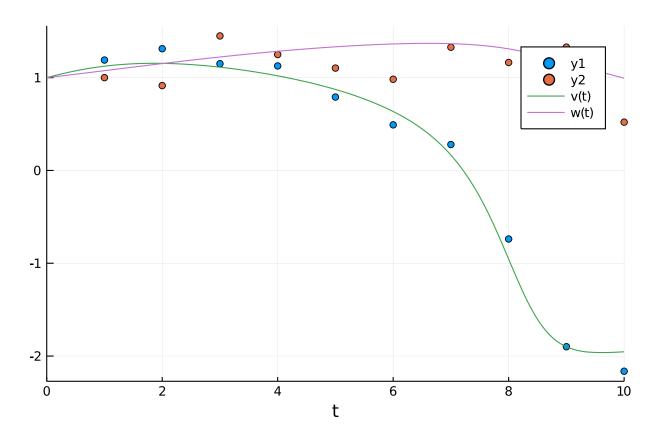
1.16338

1.32913 0.520562

#### 0.0.2 Plot of the data and the solution.

1.0002 0.91441 1.44954 1.24924

```
scatter(t, data[1,:])
scatter!(t, data[2,:])
plot!(sol)
```



#### 0.0.3 Priors for the parameters which will be passed for the Bayesian Inference

```
priors =  [truncated(Normal(1.0,0.5),0,1.5),truncated(Normal(1.0,0.5),0,1.5),truncated(Normal(0.0,0.5),0.0,0.5), \\ 4-element Array{Distributions.Truncated{Distributions.Normal{Float64},Distributions.Continuous,Float64},1}: \\ Truncated(Distributions.Normal{Float64}(\mu=1.0, \sigma=0.5), range=(0.0, 1.5)) \\ Truncated(Distributions.Normal{Float64}(\mu=1.0, \sigma=0.5), range=(0.0, 1.5)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.0, \sigma=0.5), range=(0.0, 0.5)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.5, \sigma=0.5), range=(0.0, 1.0)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.0, \sigma=0.5), range=(0.0, 1.0)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.0, \sigma=0.5), range=(0.0, 1.0)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.5, \sigma=0.5), range=(0.0, 1.0)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.5, \sigma=0.5), range=(0.0, 1.0)) \\ Truncated(Distributions.Normal{Float64}(\mu=0.0, \sigma=0.5), range=(0.0, 0.5)) \\ Truncated(Distribut
```

#### 0.0.4 Benchmarks

```
@btime bayesian_result_stan =
stan_inference(prob_ode_fitzhughnagumo,t,data,priors;num_samples =
10_000,printsummary=false)
File /builds/JuliaGPU/DiffEqBenchmarks.jl/tmp/parameter_estimation_model.st
an will be updated.
Error: IOError: chdir : no such file or directory (ENOENT)

@btime bayesian_result_turing =
turing_inference(prob_ode_fitzhughnagumo,Tsit5(),t,data,priors;num_samples = 10_000)
26.265 s (247496000 allocations: 18.03 GiB)
```

Object of type Chains, with data of type  $9000 \times 17 \times 1 \text{ Array}\{Float64,3\}$ 

```
Iterations
            = 1:9000
Thinning interval = 1
Chains
Samples per chain = 9000
internals
            = acceptance_rate, hamiltonian_energy, hamiltonian_energy
_error, is_accept, log_density, lp, max_hamiltonian_energy_error, n_steps,
nom_step_size, numerical_error, step_size, tree_depth
parameters
                 = theta[1], theta[2], theta[3], theta[4], \sigma[1]
2-element Array{MCMCChains.ChainDataFrame,1}
Summary Statistics
 parameters
               mean
                       std naive_se
                                        mcse
                                                   ess
                                                        r_hat
   theta[1] 0.8421 0.3154
                              0.0033 0.0056 3095.8740 1.0000
   theta[2] 1.0263 0.2774
                              0.0029 0.0050 3035.1889 0.9999
   theta[3] 0.0942 0.0431
                              0.0005 0.0010 1825.3637 1.0001
   theta[4] 0.4791 0.0760
                              0.0008 0.0018 1991.5666 1.0001
       \sigma[1] 0.2884 0.0572
                              0.0006 0.0009 2780.1061 1.0001
Quantiles
              2.5% 25.0%
                                     75.0%
                            50.0%
                                            97.5%
 parameters
   theta[1] 0.1939 0.6280
                            0.8609 1.0743 1.4061
   theta[2] 0.4381 0.8404
                            1.0541 1.2433 1.4575
   theta[3] 0.0229 0.0634 0.0901 0.1198 0.1894
   theta[4] 0.3475 0.4266 0.4735 0.5247 0.6414
       \sigma[1] 0.2017 0.2479 0.2798 0.3195 0.4230
```

## 1 Conclusion

FitzHugh-Ngumo is a standard problem for parameter estimation studies. In the FitzHugh-Nagumo model the parameters to be estimated were [0.7,0.8,0.08,0.5]. dynamichmc\_inference has issues with the model and hence was excluded from this benchmark.

```
using DiffEqBenchmarks
DiffEqBenchmarks.bench_footer(WEAVE_ARGS[:folder],WEAVE_ARGS[:file])
```

# 1.1 Appendix

These benchmarks are a part of the DiffEqBenchmarks.jl repository, found at: https://github.com/JuliaDenchmarks.jl repository,

```
using DiffEqBenchmarks
DiffEqBenchmarks.weave_file("ParameterEstimation","DiffEqBayesFitzHughNagumo.jmd")
```

Computer Information:

```
Julia Version 1.4.2
Commit 44fa15b150* (2020-05-23 18:35 UTC)
Platform Info:
    OS: Linux (x86_64-pc-linux-gnu)
    CPU: Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz
    WORD_SIZE: 64
    LIBM: libopenlibm
    LLVM: libLLVM-8.0.1 (ORCJIT, skylake)
Environment:
    JULIA_DEPOT_PATH = /builds/JuliaGPU/DiffEqBenchmarks.jl/.julia
    JULIA_CUDA_MEMORY_LIMIT = 2147483648
    JULIA_PROJECT = @.
    JULIA_NUM_THREADS = 8
```

#### Package Information:

```
Status: `/builds/JuliaGPU/DiffEqBenchmarks.jl/benchmarks/ParameterEstimation/Project.to
[6e4b80f9-dd63-53aa-95a3-0cdb28fa8baf] BenchmarkTools 0.5.0
[a134a8b2-14d6-55f6-9291-3336d3ab0209] BlackBoxOptim 0.5.0
[593b3428-ca2f-500c-ae53-031589ec8ddd] CmdStan 6.0.6
[ebbdde9d-f333-5424-9be2-dbf1e9acfb5e] DiffEqBayes 2.16.0
[1130ab10-4a5a-5621-a13d-e4788d82bd4c] DiffEqParamEstim 1.15.0
[ef61062a-5684-51dc-bb67-a0fcdec5c97d] DiffEqUncertainty 1.4.1
[31c24e10-a181-5473-b8eb-7969acd0382f] Distributions 0.23.4
[bbc10e6e-7c05-544b-b16e-64fede858acb] DynamicHMC 2.1.5
[76087f3c-5699-56af-9a33-bf431cd00edd] NLopt 0.6.0
[1dea7af3-3e70-54e6-95c3-0bf5283fa5ed] OrdinaryDiffEq 5.41.0
[65888b18-ceab-5e60-b2b9-181511a3b968] ParameterizedFunctions 5.3.0
[91a5bcdd-55d7-5caf-9e0b-520d859cae80] Plots 1.5.3
[731186ca-8d62-57ce-b412-fbd966d074cd] RecursiveArrayTools 2.5.0
```