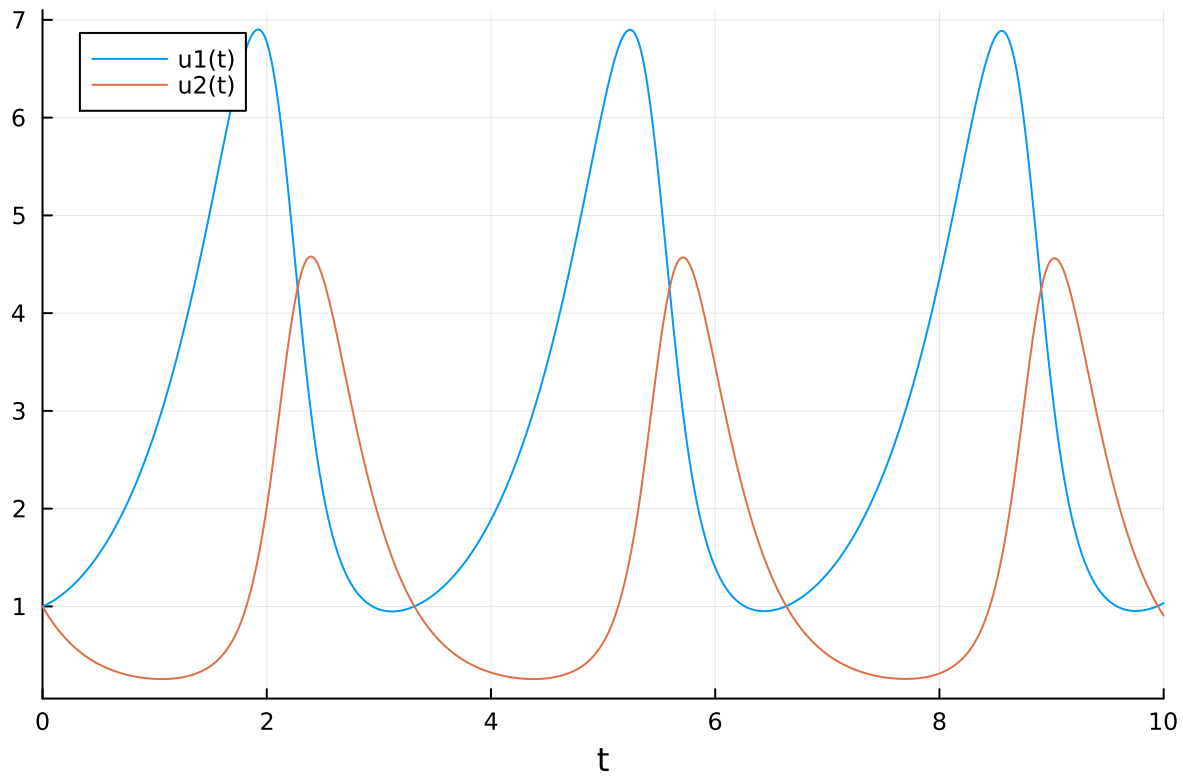


```
1 begin
2   import Pkg
3   Pkg.activate("/home/noams/repositories/neurohelp/neurohelp-julia-
   codebase/DelayedDifferentialAnalysis")
4 end
```

```
Activating project at `~/repositories/neurohelp/neurohelp-julia-codebas
e/DelayedDifferentialAnalysis`
```

TaskLocalRNG()

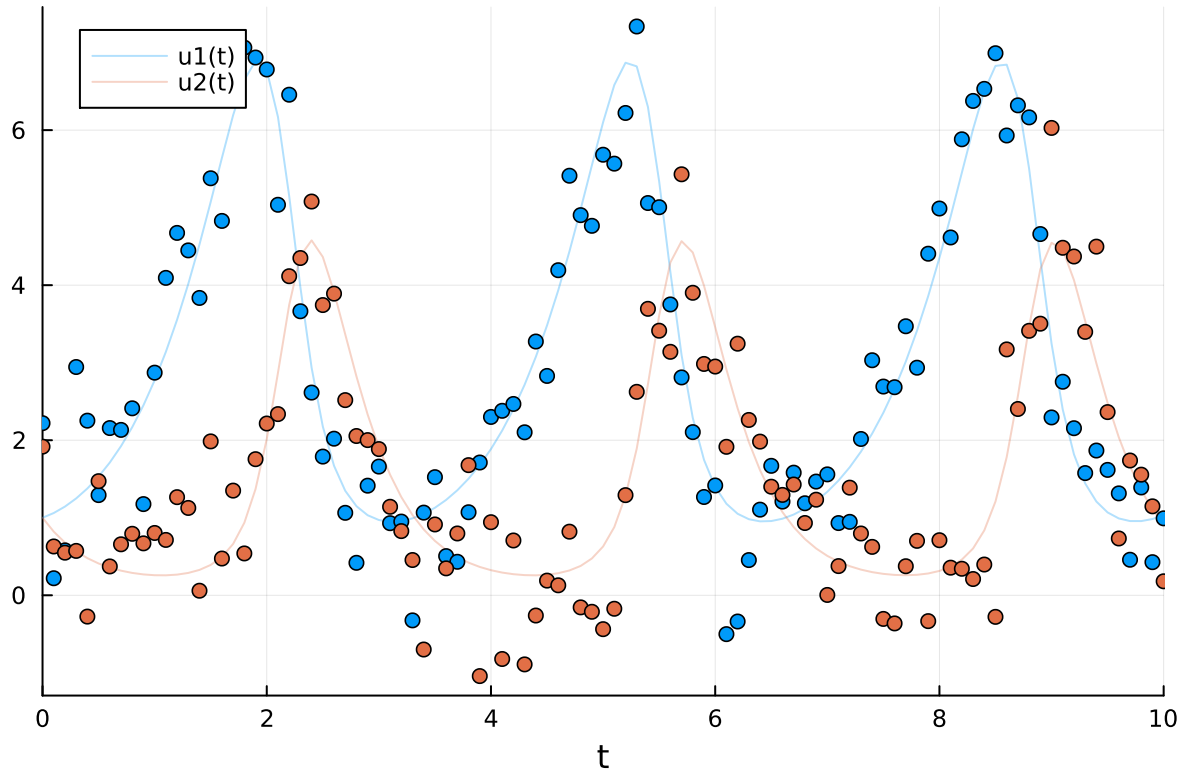
```
1 begin
2   using Turing
3   using DifferentialEquations
4   using StatsPlots
5   using LinearAlgebra
6   using Random
7   using PlutoUI
8   using Zarr
9   using Printf
10  # using CUDA
11  # using CuArrays
12  # using TopoPlots
13  # using Neuroimaging
14  Random.seed!(16);
15 end
```



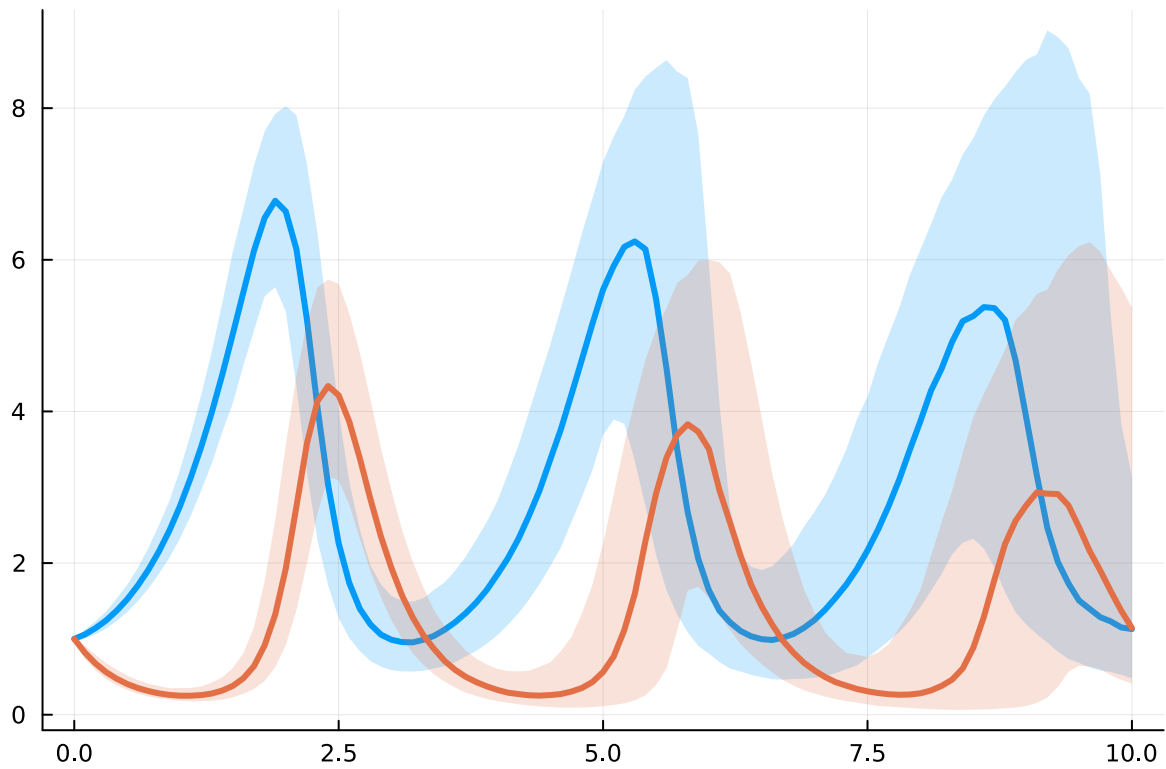
```

1 begin
2   # Define Lotka-Volterra model.
3   function lotka_volterra(du, u, p, t)
4     # Model parameters.
5      $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$  = p
6     # Current state.
7     x, y = u
8
9     # Evaluate differential equations.
10    du[1] = ( $\alpha$  -  $\beta$  * y) * x # prey
11    du[2] = ( $\delta$  * x -  $\gamma$ ) * y # predator
12
13    return nothing
14  end
15
16  # Define initial-value problem.
17  u0 = [1.0, 1.0]
18  p = [1.5, 1.0, 3.0, 1.0]
19  tspan = (0.0, 10.0)
20  prob = ODEProblem(lotka_volterra, u0, tspan, p)
21
22  # Plot simulation.
23  plot(solve(prob, Tsit5()))
24 end

```



```
1 begin
2   sol = solve(prob, Tsit5(); saveat=0.1)
3   odedata = Array(sol) + 0.6 * randn(size(Array(sol)))
4   # Plot simulation and noisy observations.
5   plot(sol; alpha=0.3)
6   scatter!(sol.t, odedata'; color=[1 2], label="")
7 end
```



```

1 begin
2   function multiplicative_noise!(du, u, p, t)
3     x, y = u
4     du[1] = p[5] * x
5     du[2] = p[6] * y
6   end
7   p_sde = [1.5, 1.0, 3.0, 1.0,  $\sigma_1$ ,  $\sigma_2$ ]
8
9   function lotka_volterra!(du, u, p, t)
10    x, y = u
11     $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$  = p
12    du[1] = dx =  $\alpha$  * x -  $\beta$  * x * y
13    du[2] = dy =  $\delta$  * x * y -  $\gamma$  * y
14  end
15
16  prob_sde = SDEProblem(lotka_volterra!, multiplicative_noise!, u0, tspan, p_sde)
17
18  ensembleprob = EnsembleProblem(prob_sde)
19  data = solve(ensembleprob, SOSRI(); saveat=0.1, trajectories=1000)
20  plot(EnsembleSummary(data))
21 end

```

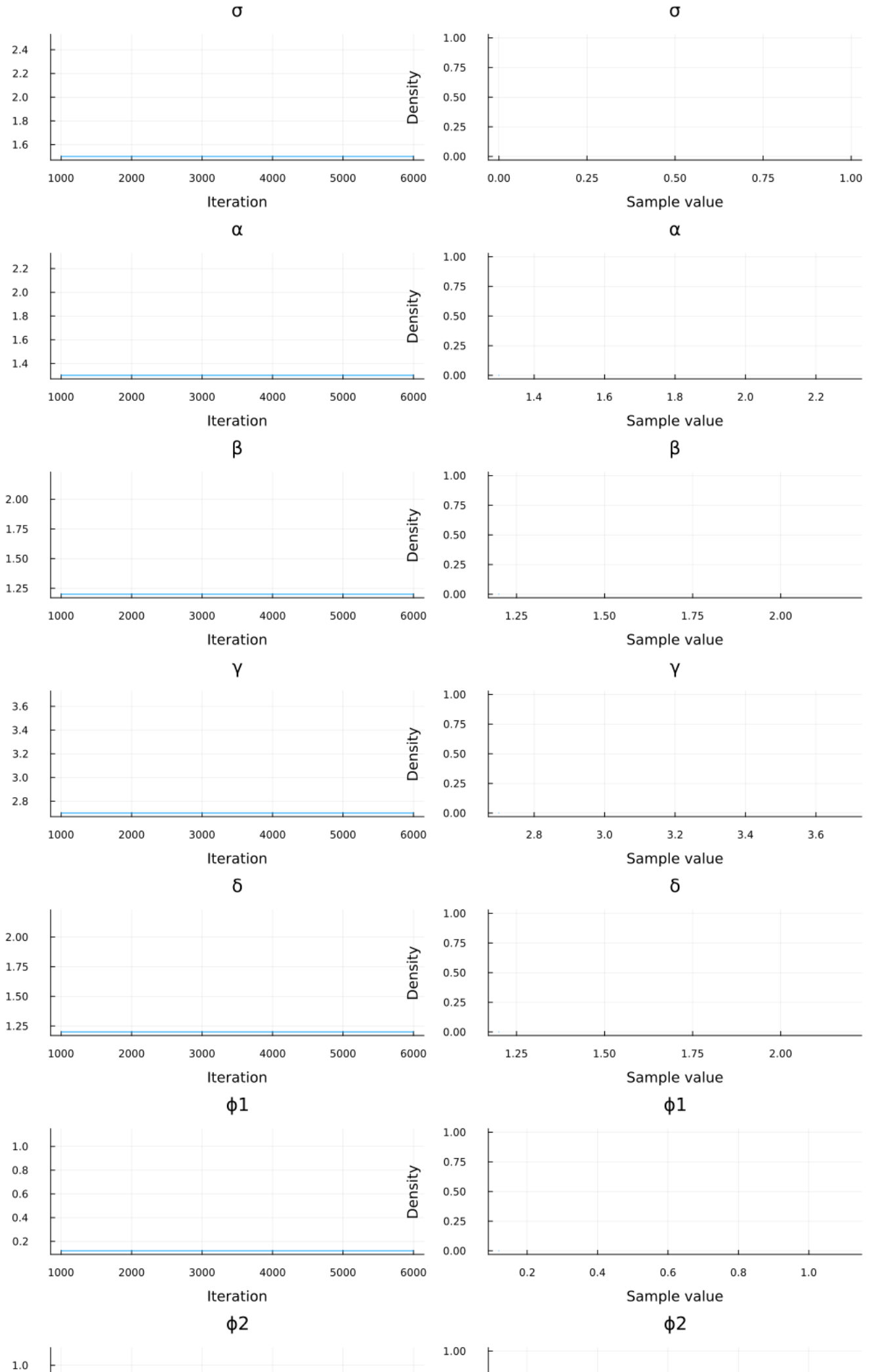
0.1

1 @bind  $\sigma_1$  Slider(0:0.1:1, default=0.1, show\_value=true)

0.2

1 @bind  $\sigma_2$  Slider(0:0.1:1, default=0.1, show\_value=true)

```
1 @model function fitlv_sde(data, prob)
2   # Prior distributions.
3    $\sigma$  ~ InverseGamma(2, 3)
4    $\alpha$  ~ truncated(Normal(1.3, 0.5), 0.5, 2.5)
5    $\beta$  ~ truncated(Normal(1.2, 0.25), 0.5, 2)
6    $\gamma$  ~ truncated(Normal(3.2, 0.25), 2.2, 4.0)
7    $\delta$  ~ truncated(Normal(1.2, 0.25), 0.5, 2.0)
8    $\phi_1$  ~ truncated(Normal(0.12, 0.3), 0.05, 0.25)
9    $\phi_2$  ~ truncated(Normal(0.12, 0.3), 0.05, 0.25)
10
11  # Simulate stochastic Lotka-Volterra model.
12  p = [ $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$ ,  $\phi_1$ ,  $\phi_2$ ]
13  predicted = solve(prob, SOSRI(); p=p, saveat=0.1)
14
15  # Early exit if simulation could not be computed successfully.
16  if predicted.retcode != :Success
17    Turing.@addlogprob! -Inf
18    return nothing
19  end
20
21  # Observations.
22  for i in 1:length(predicted)
23    data[:, i] ~ MvNormal(predicted[i],  $\sigma^2 * I$ )
24  end
25
26  return nothing
27 end;
```



```
1 begin
2     model_sde = fitlv_sde(odedata, prob_sde)
3
4     setadbackend(:forwarddiff)
5     chain_sde = sample(
6         model_sde,
7         NUTS(0.25),
8         5000;
9         init_params=[1.5, 1.3, 1.2, 2.7, 1.2, 0.12, 0.12],
10        progress=false,
11    )
12    plot(chain_sde)
13 end
```

Found initial step size

$\epsilon$ : 0.07500000000000001

Incorrect  $\epsilon$  = NaN;  $\epsilon_{\text{previous}}$  = 0.07500000000000001 is used instead.

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1 Enter cell code...

