

DifferentialEquations.jl Workshop Exercise Solutions

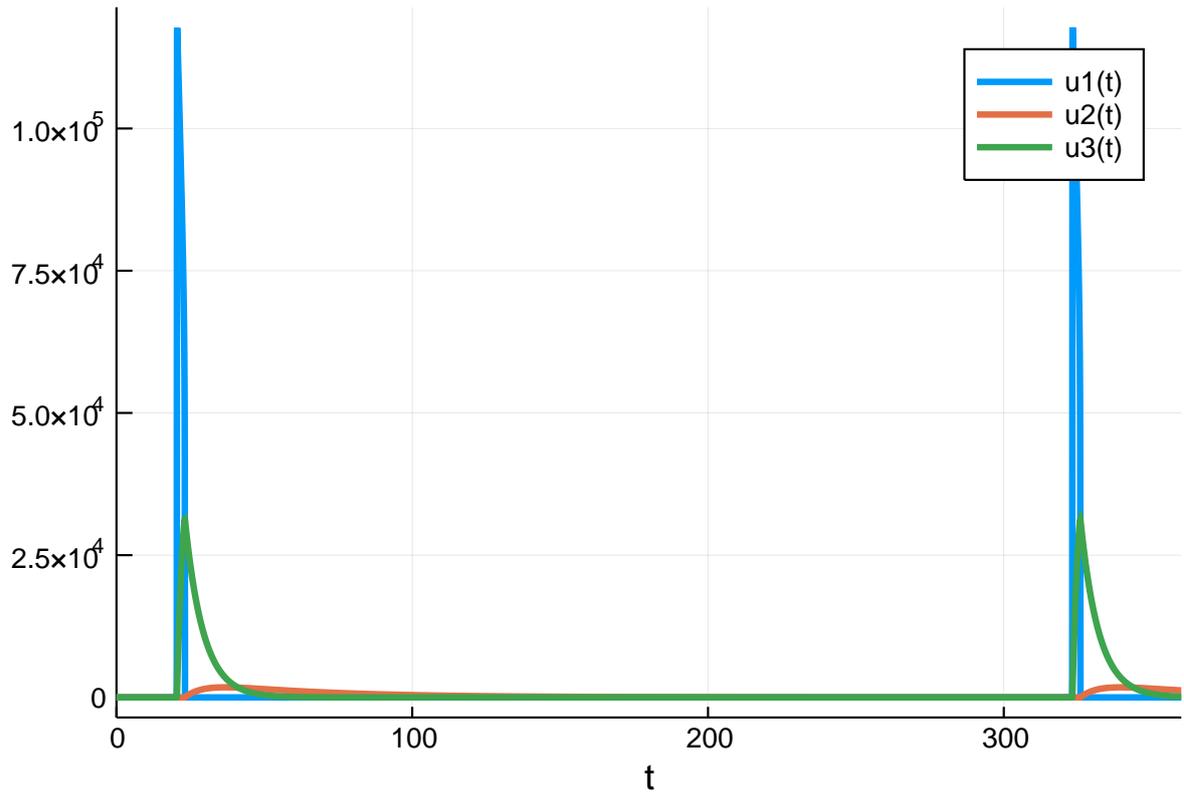
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July 15, 2019

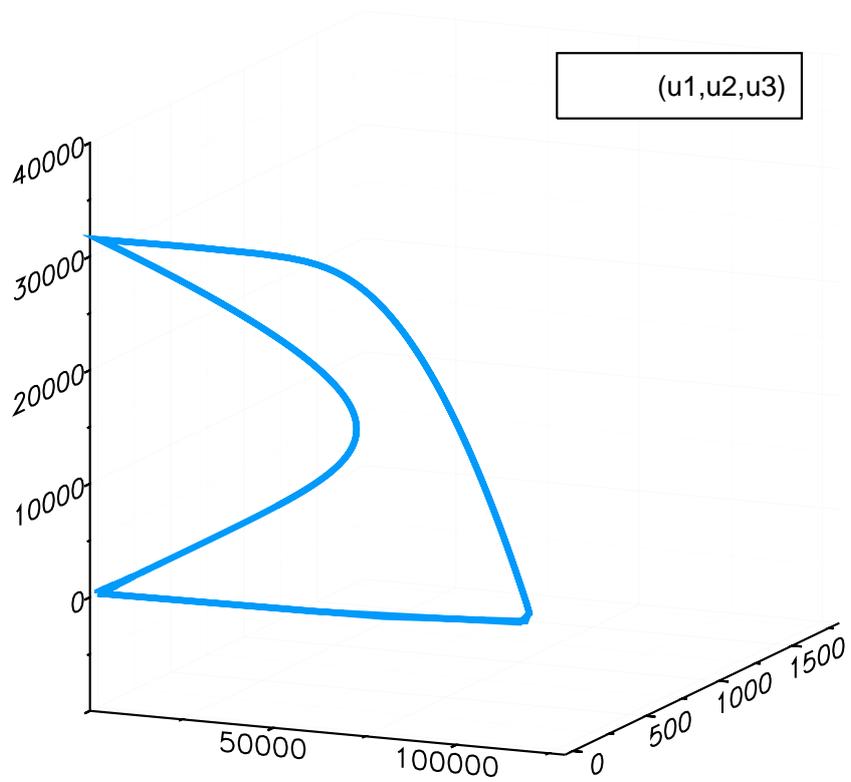
1 Problem 1: Investigating Sources of Randomness and Uncertainty in a Biological System

1.1 Part 1: Simulating the Oregonator ODE model

```
using DifferentialEquations, Plots
function orego(du,u,p,t)
    s,q,w = p
    y1,y2,y3 = u
    du[1] = s*(y2+y1*(1-q*y1-y2))
    du[2] = (y3-(1+y1)*y2)/s
    du[3] = w*(y1-y3)
end
p = [77.27,8.375e-6,0.161]
prob = ODEProblem(orego,[1.0,2.0,3.0],[0.0,360.0],p)
sol = solve(prob)
plot(sol)
```



```
plot(sol, vars=(1,2,3))
```



1.2 Part 2: Investigating Stiffness

```
using BenchmarkTools
```

```
prob = ODEProblem(orego, [1.0, 2.0, 3.0], (0.0, 50.0), p)
@btime sol = solve(prob, Tsit5())
```

3.134 s (8723181 allocations: 920.68 MiB)

retcode: Success

Interpolation: specialized 4th order "free" interpolation

t: 872306-element Array{Float64,1}:

```
0.0
0.016189218375969157
0.023553748136851134
0.038180267679755686
0.050503297498957454
0.06810643682329323
0.08676314534460629
0.11145303081419239
0.1410587592990862
0.18104737342146363
```

⋮

```
49.99977332573522
49.9998045817995
49.999835837885485
49.99986709399317
49.99989835012255
49.99992960627363
49.999960862446414
49.9999921186409
50.0
```

u: 872306-element Array{Array{Float64,1},1}:

```
[1.0, 2.0, 3.0]
[1.71286, 1.99961, 2.99591]
[1.83763, 1.99937, 2.99447]
[1.94804, 1.99883, 2.99191]
[1.98078, 1.99836, 2.98988]
[1.99652, 1.99768, 2.98705]
[2.00125, 1.99696, 2.98409]
[2.00327, 1.996, 2.98019]
[2.00461, 1.99484, 2.97555]
[2.0062, 1.99328, 2.96932]
```

⋮

```
[1.00114, 1453.02, 414.832]
[1.00114, 1453.02, 414.83]
[1.00114, 1453.02, 414.828]
[1.00114, 1453.01, 414.826]
[1.00114, 1453.01, 414.824]
[1.00114, 1453.01, 414.822]
[1.00114, 1453.01, 414.82]
[1.00114, 1453.01, 414.818]
[1.00088, 1453.01, 414.817]
```

```
@btime sol = solve(prob, Rodas5())
```

544.899 μ s (2920 allocations: 175.86 KiB)

retcode: Success

Interpolation: 3rd order Hermite

t: 110-element Array{Float64,1}:

```
0.0
0.019615259849088615
0.029598267922660175
```

```

0.047052910887750835
0.06489945147114441
0.08933211282883743
0.12069352237075688
0.16655179061086892
0.24088874148540496
0.39558172278217235
:
26.75710407571649
27.982394888737232
29.7694090380865
32.21886344926688
35.09441917419525
38.498626966839055
42.33882931016379
46.609195570565284
50.0
u: 110-element Array{Array{Float64,1},1}:
 [1.0, 2.0, 3.0]
 [1.78041, 1.9995, 2.99522]
 [1.89877, 1.99915, 2.99338]
 [1.97458, 1.9985, 2.99044]
 [1.995, 1.99781, 2.98756]
 [2.0016, 1.99686, 2.98368]
 [2.00375, 1.99564, 2.97874]
 [2.00564, 1.99384, 2.97157]
 [2.00859, 1.99093, 2.9601]
 [2.01481, 1.98485, 2.93677]
 :
 [1.00095, 1052.21, 17454.4]
 [1.00079, 1266.47, 14329.7]
 [1.00067, 1490.32, 10747.2]
 [1.0006, 1670.97, 7245.14]
 [1.00057, 1758.48, 4560.57]
 [1.00057, 1757.6, 2636.71]
 [1.00059, 1683.83, 1421.32]
 [1.00064, 1561.03, 715.164]
 [1.00069, 1452.9, 414.722]

```

1.3 (Optional) Part 3: Specifying Analytical Jacobians (I)

1.4 (Optional) Part 4: Automatic Symbolicification and Analytical Jacobian Calculations

1.5 Part 5: Adding stochasticity with stochastic differential equations

```

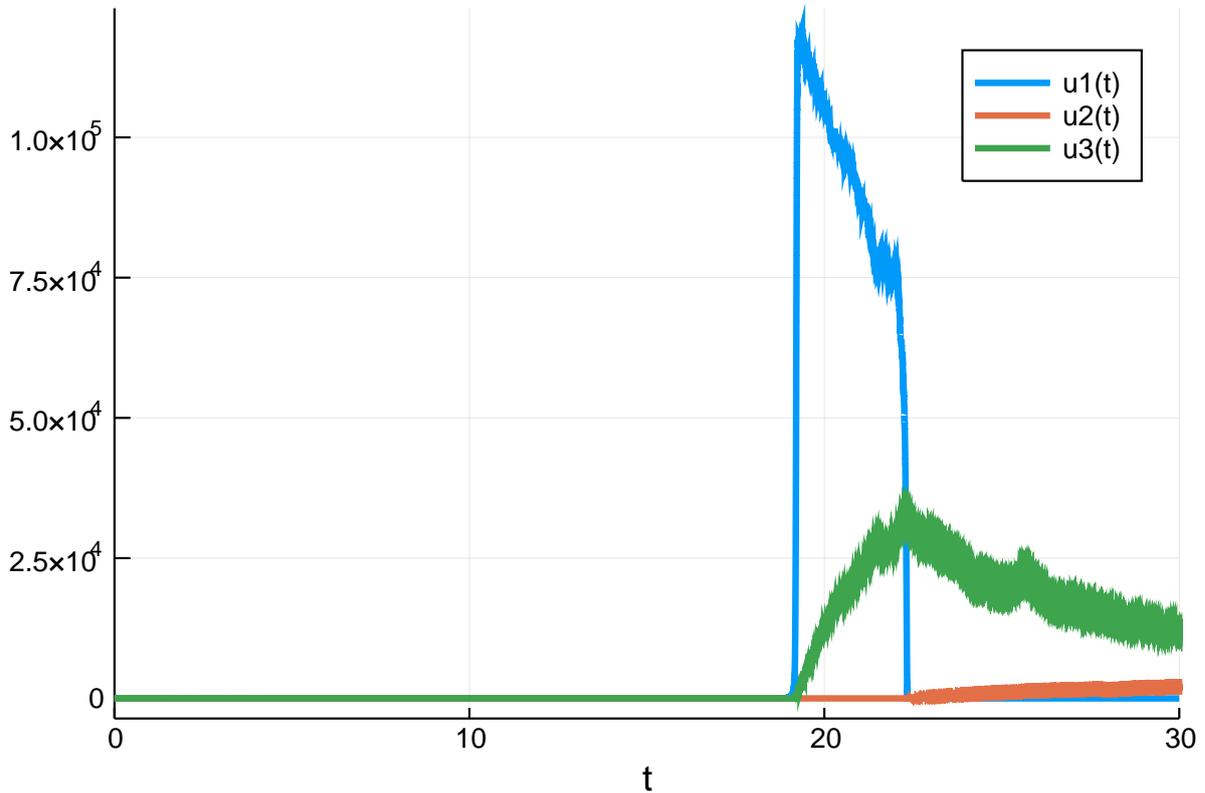
function orego(du,u,p,t)
    s,q,w = p
    y1,y2,y3 = u
    du[1] = s*(y2+y1*(1-q*y1-y2))
    du[2] = (y3-(1+y1)*y2)/s
    du[3] = w*(y1-y3)
end
function g(du,u,p,t)

```

```

du[1] = 0.1u[1]
du[2] = 0.1u[2]
du[3] = 0.1u[3]
end
p = [77.27,8.375e-6,0.161]
prob = SDEProblem(orego,g,[1.0,2.0,3.0],(0.0,30.0),p)
sol = solve(prob,SOSRI())
plot(sol)

```



```
sol = solve(prob,ImplicitRKMil()); plot(sol)
```

```
sol = solve(prob,ImplicitRKMil()); plot(sol)
```

1.6 Part 6: Gillespie jump models of discrete stochasticity

1.7 Part 7: Probabilistic Programming / Bayesian Parameter Estimation with DiffEqBayes.jl + Turing.jl (I)

The data was generated with:

```

function orego(du,u,p,t)
    s,q,w = p
    y1,y2,y3 = u
    du[1] = s*(y2+y1*(1-q*y1-y2))
    du[2] = (y3-(1+y1)*y2)/s
    du[3] = w*(y1-y3)
end
p = [60.0,1e-5,0.2]
prob = ODEProblem(orego,[1.0,2.0,3.0],(0.0,30.0),p)
sol = solve(prob,Rodas5(), abstol=1/10^14, reltol=1/10^14)

```

```

retcode: Success
Interpolation: 3rd order Hermite
t: 48799-element Array{Float64,1}:
 0.0
 0.00013773444266123363
 0.000201070235058078
 0.0003020539265117362
 0.0004030376179653944
 0.000505840575661047
 0.0006092634319273482
 0.0007136360693805303
 0.0008186320050683297
 0.000924255465457595
  ⋮
29.79488308974022
29.82256859717493
29.850254104609636
29.877939612044344
29.90562511947905
29.93331062691376
29.960996134348466
29.988681641783174
30.0
u: 48799-element Array{Array{Float64,1},1}:
 [1.0, 2.0, 3.0]
 [1.00823, 2.0, 2.99995]
 [1.01199, 2.0, 2.99992]
 [1.01796, 1.99999, 2.99988]
 [1.02389, 1.99999, 2.99984]
 [1.02989, 1.99999, 2.9998]
 [1.0359, 1.99999, 2.99976]
 [1.04191, 1.99999, 2.99972]
 [1.04793, 1.99999, 2.99968]
 [1.05395, 1.99998, 2.99964]
  ⋮
 [1.00065, 1541.44, 2708.42]
 [1.00065, 1541.27, 2693.47]
 [1.00065, 1541.08, 2678.6]
 [1.00065, 1540.89, 2663.82]
 [1.00065, 1540.7, 2649.12]
 [1.00065, 1540.49, 2634.49]
 [1.00065, 1540.28, 2619.95]
 [1.00065, 1540.07, 2605.49]
 [1.00065, 1539.98, 2599.6]

```

1.8 (Optional) Part 8: Using DiffEqBiological's Reaction Network DSL

2 Problem 2: Fitting Hybrid Delay Pharmacokinetic Models with Automated Responses (B)

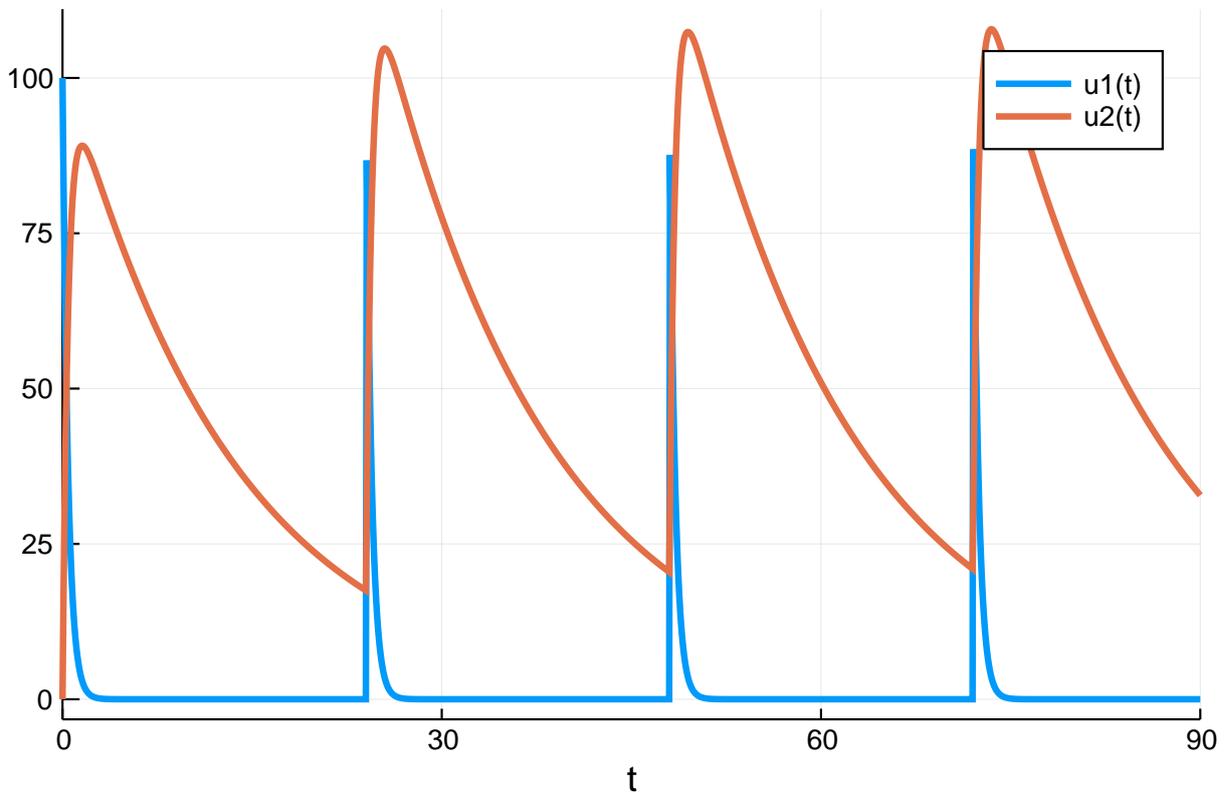
2.1 Part 1: Defining an ODE with Predetermined Doses

```

function onecompartment(du,u,p,t)
    Ka,Ke = p
    du[1] = -Ka*u[1]
    du[2] = Ka*u[1] - Ke*u[2]
end
p = (Ka=2.268,Ke=0.07398)
prob = ODEProblem(onecompartment,[100.0,0.0],[0.0,90.0],p)

tstops = [24,48,72]
condition(u,t,integrator) = t ∈ tstops
affect!(integrator) = (integrator.u[1] += 100)
cb = DiscreteCallback(condition,affect!)
sol = solve(prob,Tsit5(),callback=cb,tstops=tstops)
plot(sol)

```



2.2 Part 2: Adding Delays

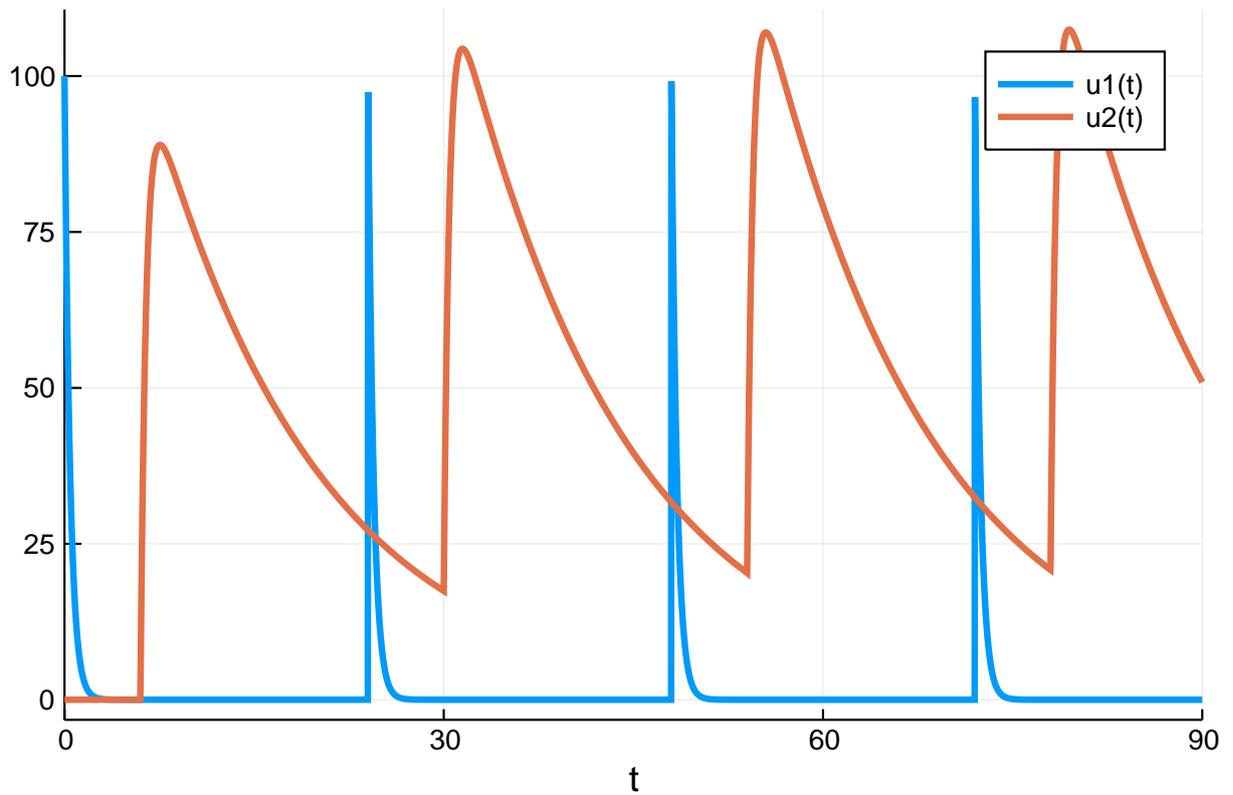
```

function onecompartment_delay(du,u,h,p,t)
    Ka,Ke,τ = p
    delayed_depot = h(p,t-τ)[1]
    du[1] = -Ka*u[1]
    du[2] = Ka*delayed_depot - Ke*u[2]
end
p = (Ka=2.268,Ke=0.07398,τ=6.0)
h(p,t) = [0.0,0.0]
prob = DDEProblem(onecompartment_delay,[100.0,0.0],h,(0.0,90.0),p)

tstops = [24,48,72]
condition(u,t,integrator) = t ∈ tstops
affect!(integrator) = (integrator.u[1] += 100)
cb = DiscreteCallback(condition,affect!)
sol = solve(prob,MethodOfSteps(Rosenbrock23()),callback=cb,tstops=tstops)

```

```
plot(sol)
```



2.3 Part 3: Automatic Differentiation (AD) for Optimization (I)

2.4 Part 4: Fitting Known Quantities with DiffEqParamEstim.jl + Optim.jl

The data was generated with

```
p = (Ka = 0.5, Ke = 0.1, τ = 4.0)
```

```
(Ka = 0.5, Ke = 0.1, τ = 4.0)
```


- 2.5 Part 5: Implementing Control-Based Logic with Continuous-Callbacks (I)
- 2.6 Part 6: Global Sensitivity Analysis with the Morris and Sobol Methods
- 3 Problem 3: Differential-Algebraic Equation Modeling of a Double Pendulum (B)
 - 3.1 Part 1: Simple Introduction to DAEs: Mass-Matrix Robertson Equations
 - 3.2 Part 2: Solving the Implicit Robertson Equations with IDA
 - 3.3 Part 3: Manual Index Reduction of the Single Pendulum
 - 3.4 Part 4: Single Pendulum Solution with IDA
 - 3.5 Part 5: Solving the Double Penulum DAE System
- 4 Problem 4: Performance Optimizing and Parallelizing Semilinear PDE Solvers (I)
 - 4.1 Part 1: Implementing the BRUSS PDE System as ODEs
 - 4.2 Part 2: Optimizing the BRUSS Code
 - 4.3 Part 3: Exploiting Jacobian Sparsity with Color Differentiation
 - 4.4 (Optional) Part 4: Structured Jacobians
 - 4.5 (Optional) Part 5: Automatic Symbolicification and Analytical Jacobian
 - 4.6 Part 6: Utilizing Preconditioned-GMRES Linear Solvers
 - 4.7 Part 7: Exploring IMEX and Exponential Integrator Techniques (E)
 - 4.8 Part 8: Work-Precision Diagrams for Benchmarking Solver Choices
 - 4.9 Part 9: GPU-Parallelism for PDEs (E)
 - 4.10 Part 10: Adjoint Sensitivity Analysis for Gradients of PDEs