

Mass-Spring Underdamped Oscillator

$$m \frac{d^2 x}{dt^2} + c \frac{dx}{dt} + kx = 0$$

$$x(0) = 1$$

$$\frac{dx}{dt}(0) = 0$$

```

1 begin
2     using NeuralPDE
3     using LinearAlgebra
4     using Plots
5     # using Flux
6     using Lux, Optimization
7     import OptimizationOptimisers
8     import ModelingToolkit: Interval
9     using CUDA, Random, ComponentArrays
10    using OptimizationOptimJL
11 end

```

Differential(t) ∘ Differential(t)

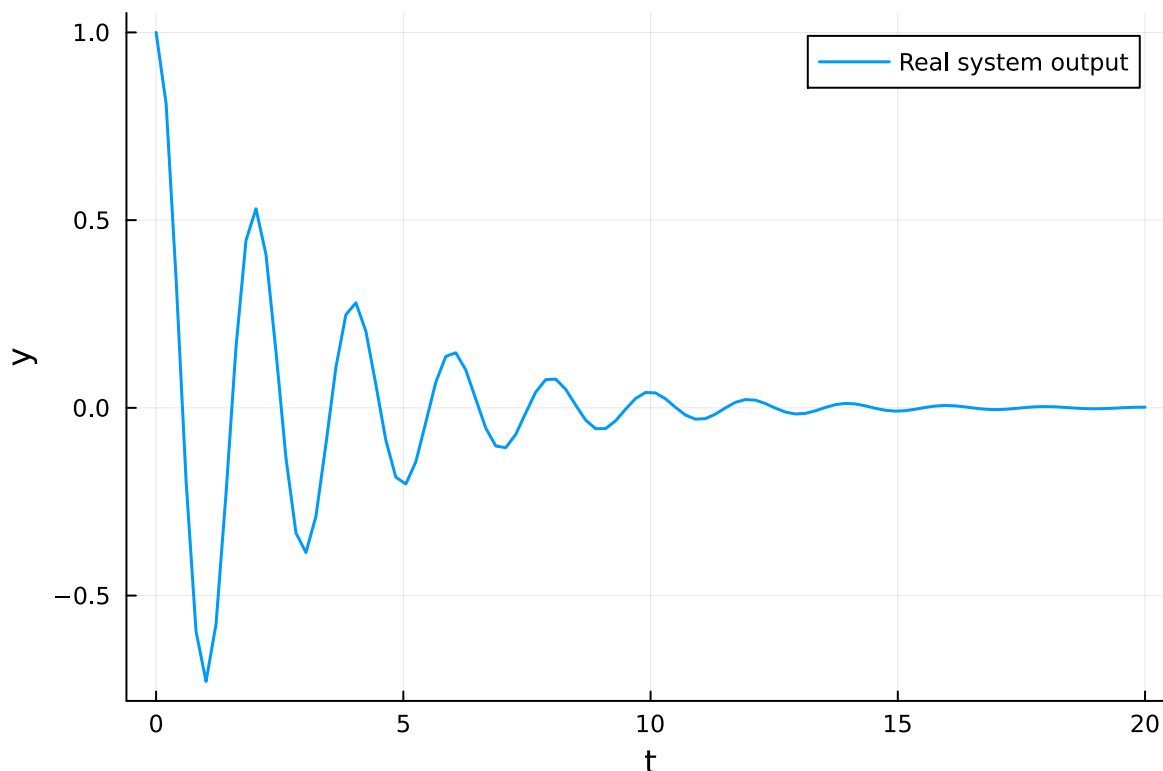
```

1 begin
2     @parameters t
3     @variables y(..)
4     Dt = Differential(t)
5     Dtt = Differential(t)^2
6 end

```

use_gpu = false

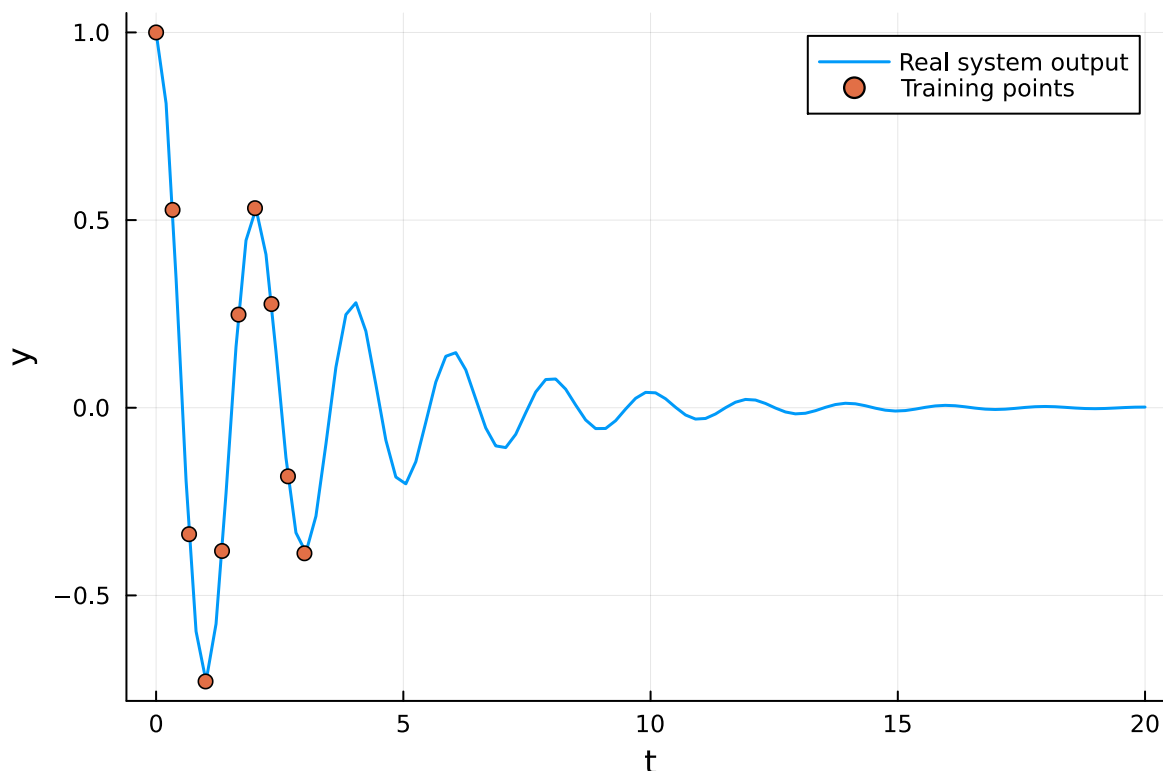
```
1 use_gpu = false
```



```

1 begin
2     # Mass-spring-damper system parameters
3     m = 2.0
4     k = 20.0
5     ζ = 0.1 # Smaller damping ratio for slower energy dissipation
6     c = 2 * ζ * sqrt(m * k)
7
8     # Initial conditions
9     y0 = 1.0 # Initial displacement
10    v0 = 0.0 # Initial velocity
11
12    # Real system
13    t_real = range(0.0, stop=20.0, length=100)
14    ω0_real = sqrt(k / m)
15    ω_d_real = ω0_real * sqrt(1 - ζ^2)
16    exp_term_real = exp.(-ζ * ω0_real * t_real)
17    osc_term_real = cos.(ω_d_real * t_real) + (ζ / sqrt(1 - ζ^2)) * sin.(ω_d_real *
18    t_real)
19    y_real = y0 .* exp_term_real .* osc_term_real
20
21    p1 = plot(t_real, y_real, xlabel="t", ylabel="y", label="Real system output",
22    linewidth=:1.5)
23 end

```



```

1 begin
2     # Time values for training data
3     t_u = range(0.0, stop=3.0, length=10)
4
5     # Angular frequency and damping ratio
6     ω0 = sqrt(k / m)
7     ω_d = ω0 * sqrt(1 - ζ^2)
8
9     # Calculate the exponential and oscillatory components
10    exp_term = exp.(-ζ * ω0 * t_u)
11    osc_term = cos.(ω_d * t_u) + (ζ / sqrt(1 - ζ^2)) * sin.(ω_d * t_u)
12
13    initial_conditions = [y(0.0) ~ y0,
14                          Dt(y(0.0)) ~ v0]
15
16    # Training points
17    y_u = y0 .* exp_term .* osc_term
18
19    training_points = [y(t_u_) ~ y_u_ for (t_u_, y_u_) in zip(t_u, y_u)]
20
21    p2 = plot(t_real, y_real, xlabel="t", ylabel="y", label="Real system output",
22              linewidth=:1.5)
23    p2 = scatter!(t_u, y_u, label="Training points")
24 end

```

```

1 begin
2     # ODE
3     f = (y, t) -> m * Dtt(y(t)) + c * Dt(y(t)) + k * y(t)
4     eq = f(y, t) ~ 0
5
6     # PINN
7     chain = Lux.Chain(Lux.Dense(1, 64, Lux.σ),
8                       Lux.Dense(64, 64, Lux.σ),
9                       # Lux.Dense(32, 32, Lux.σ),
10                      Lux.Dense(64, 1))
11
12     if use_gpu
13         ps = Lux.setup(Random.default_rng(), chain)[1]
14         ps = ps |> ComponentArray |> Lux.gpu .|> Float64
15     end
16
17     # opt = OptimizationOptimisers.Adam(0.01)
18     opt = Optim.BFGS()
19
20     # Boundary conditions
21     boundary_conditions = vcat(initial_conditions, training_points)
22
23     # strategy = GridTraining(0.1)
24     strategy = QuasiRandomTraining(200, bcs_points=length(boundary_conditions)/2)
25     discretization = PhysicsInformedNN(chain, strategy)
26
27     domain = [t ∈ Interval(0.0, 20.0)]
28
29     @named system = PDESystem(eq, boundary_conditions, domain, [t], [y(t)])
30     prob = discretize(system, discretization)
31
32     epoch = 0
33
34     callback = function (p, l)
35         global epoch
36         epoch += 1
37         if epoch % 100 == 0
38             println("Epoch: $epoch\tLoss: $l")
39         end
40         return false
41     end
42
43     display(chain)
44 end

```

```

Chain(
  layer_1 = Dense(1 => 64, sigmoid_fast), # 128 parameters
  layer_2 = Dense(64 => 64, sigmoid_fast), # 4_160 parameters
  layer_3 = Dense(64 => 1),                # 65 parameters
)
# Total: 4_353 parameters,
# plus 0 states, summarysize 48 bytes.

```



```
res =
```

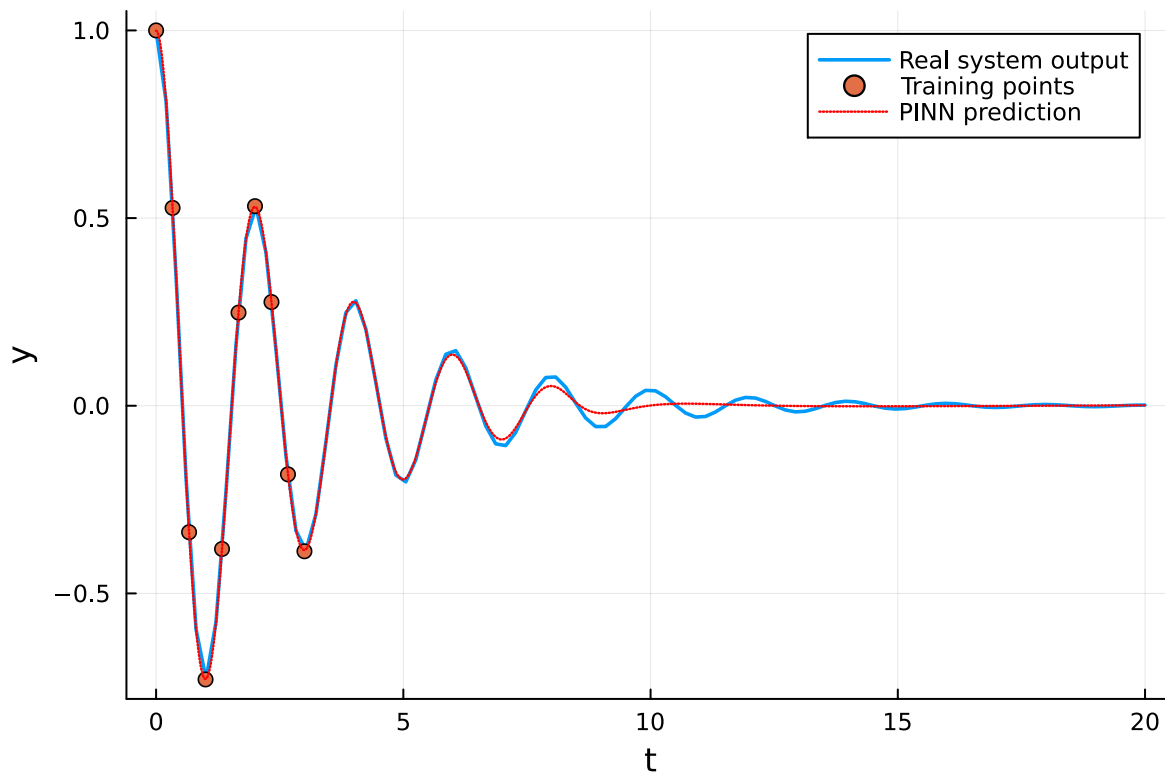
```
SciMLBase.OptimizationSolution{Float64, 1, ComponentArrays.ComponentVector{Float64, Vectc
```

```
1 res = @time Optimization.solve(prob, opt; callback=callback, maxiters=1000)
```

```
Epoch: 100 Loss: 0.7548978692910726
Epoch: 200 Loss: 0.1976231264759747
Epoch: 300 Loss: 0.07342961578671824
Epoch: 400 Loss: 0.03622208456806477
Epoch: 500 Loss: 0.021201140977161203
Epoch: 600 Loss: 0.012698842893390683
Epoch: 700 Loss: 0.009209591134113574
Epoch: 800 Loss: 0.007598321849814344
Epoch: 900 Loss: 0.006634043870866203
Epoch: 1000 Loss: 0.005845939177140362
312.166092 seconds (305.80 M allocations: 215.230 GiB, 5.18% gc time, 1.42% compilation time)
WARNING: both DomainSets and SciMLBase export "isconstant"; uses of it in module NeuralPDE must be qualified
WARNING: both DomainSets and SciMLBase export "islinear"; uses of it in module NeuralPDE must be qualified
WARNING: both DomainSets and SciMLBase export "issquare"; uses of it in module NeuralPDE must be qualified
```

```
[0.999121, 0.998624, 0.997131, 0.994649, 0.991189, 0.98676, 0.981374, 0.975041, 0.967776,
```

```
1 begin
2     phi = discretization.phi
3
4     t_span = (0.0:0.01:20.0)
5     y_predict = [first(phi([t], res.u)) for t in t_span]
6 end
```



```
1 begin
2   p3 = plot(t_real, y_real, xlabel="t", ylabel="y", label="Real system output",
3             linewidth=:1.8)
4   p3 = scatter!(t_u, y_u, label="Training points")
5   p3 = plot!(t_span, y_predict, xlabel="t", ylabel="y", label="PINN prediction",
6               linewidth=:1.2, linecolor=:red, linestyle=:dot)
7 end
```