Neural Ordinary Differential Equations with Julia

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August 25, 2020

Overview

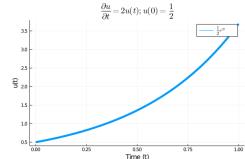
- Theory / Math
 - ODEs
 - Neural Networks
 - Neural ODEs
- 2 Julia Packages and Dataset
- Neural ODE Code and Results

Ordinary Differential Equations

Let u(t) be function in time, f function describing u's derivative $\frac{\partial u}{\partial t}$, starting at time t_0 :

$$\frac{\partial u}{\partial t} = f(u(t), t)$$
$$u(t_0) = u_0$$

with u_0 being an initial value.



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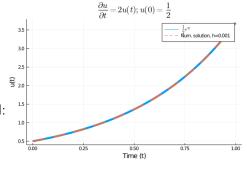
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Simulate eg. using Euler method:

$$\widetilde{u}_{t+1} = u_t + hf(u_t, t)$$

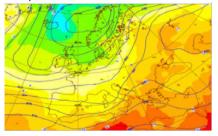
with h being a step size.



Weather Forecasting

Numerical Weather Prediction (NWP)

- PDE (space and time)
- 2 Modelling of fluid dynamics
- Navier-Stokes equations
- Computational heavy



Observations

$$u_t, u_{t+1}, u_{t+2}, \cdots$$

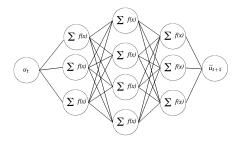
Observations

$$u_t, u_{t+1}, u_{t+2}, \cdots$$

Can we learn this?

$$f(u_t,\theta)=u_{t+1}$$

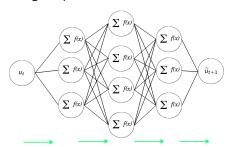
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Forward pass:

$$\widetilde{u}_{t+1} = f(u_t, \theta)$$



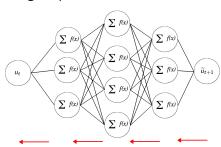
Let f be a neural network with θ being its parameters.

Forward pass:

$$\widetilde{u}_{t+1} = f(u_t,\theta)$$

Backward pass:

$$\min_{\theta} \sum_{t} \|\widetilde{u}_{t} - u_{t}\|$$



Instead of learning

$$\widetilde{u}_{t+1} = f(u_t, \theta)$$

we define an ODE

$$\frac{\partial u}{\partial t} = f(u(t), t)$$

and learn the change of u:

$$\frac{\partial u}{\partial t} = f(u_t, \theta)$$

Neural ODE:

$$\frac{\partial u}{\partial t} = f(u_t, \theta)$$

Forward pass:

$$\widetilde{u}_{t+1} = u_t + h$$
 $\underbrace{f(u_t, \theta)}_{\text{NNs forward pass}}$

Neural ODE:

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Forward pass:

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Backward pass:

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Neural ODE:

$$\frac{\partial u}{\partial t} = f(u_t, \theta)$$

Forward pass:

$$\widetilde{u}_{t+1} = u_t + hf(u_t, \theta)$$

Backward pass:

$$\min_{\theta} \sum_{t} \|u_t + hf(u_t, \theta) - u_{t+1}\|$$

Neural ODE:

$$\frac{\partial u}{\partial t} = f(u_t, \theta)$$

Forward pass:

$$\widetilde{u}_{t+1} = u_t + hf(u_t, \theta)$$

Backward pass (two steps):

$$\min_{\theta} \sum_{t} \|u_t + hf(u_t, \theta) + hf(u_t + hf(u_t, \theta), \theta) - u_{t+2}\|$$

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Julia Packages



Flux.jl

- Machine learning in Julia
- Neural Networks, MLP, DL, ...
- Derivative computation
- GPU support
- ..

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DifferentialEquations.jl

- Define diff. equations
- Equation solvers
- ODEs, SODEs, PDEs, ...
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- ...

Julia Packages



Flux.jl

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- and more!

DiffEqFlux.jl

- Combination of the twoBy authors of the two
- Implementation of [1]
- By authors of [1]

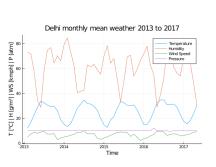
DifferentialEquations.jl

- Define diff. equations
 - Equation solvers
 - ODEs, SODEs, PDEs, \dots
 - GPU support
 - and more!

[1] Chen, Ricky TQ, et al. "Neural ordinary differential equations." Advances in neural information processing systems. 2018.

Dataset

Daily climate data in the city of Delhi from 2013 to 2017. Includes mean temperature, humidity, wind speed, mean air pressure.

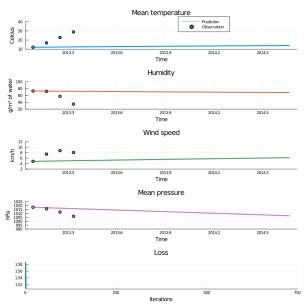


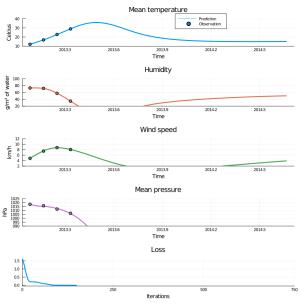


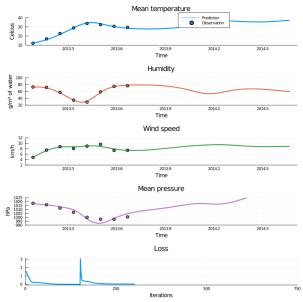
Julia Code

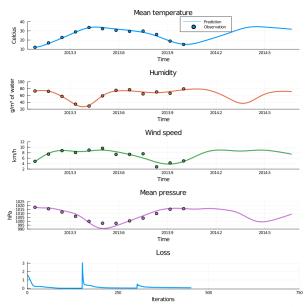
Julia Code

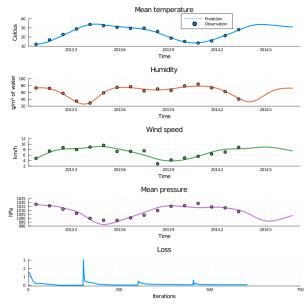
```
using OrdinaryDiffEq, Flux
function train one round(node, \theta, u, opt, maxiters,
                   u0 = data[:, 1])
    predict(\theta) = Array(node(u0, \theta))
    loss(\theta) = begin
         \hat{u} = predict(\theta)
         Flux.mse(û, u)
    end
    \theta = \theta == nothing ? node.p : \theta
    res = DiffEqFlux.sciml train(
         loss, θ, opt,
         maxiters = maxiters
    return res.minimizer
end
node = neural ode(train t, 4)
\theta = train one round(node, \theta, train u, ADAMW(1e-2), 150)
```

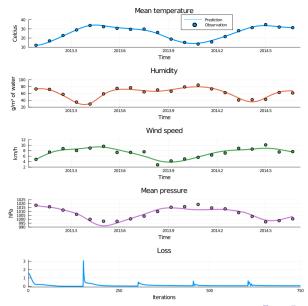


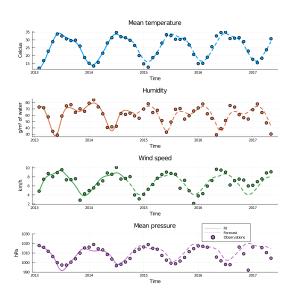












References

- Chen, Ricky TQ, et al. "Neural ordinary differential equations." Advances in neural information processing systems. 2018.
- ② DiffEqFlux Package https://github.com/SciML/DifferentialEquations.jl
- OiffEqFlux Paper Chris Rackauckas et al. "DiffEqFlux.jl - A Julia Library for Neural Differential Equations", arXiv:1902.02376
- Original Blog post this talk is based on sebastiancallh.github.io/post/neural-ode-weather-forecast/
- Stink to talk + my code github.com/nicolasholland/VariousProjects/tree/master/Neural ODE Talk
- kaggel dataset www.kaggle.com/sumanthvrao/daily-climate-time-series-data