



UNDERSTANDING NEURAL NETWORKS: A FROM SCRATCH IMPLEMENTATION IN Julia

2nd International Conference on Smart Industry, Technology and Environment

Abdelbacet Mhamdi

Dr.-Ing. in EE – MT @ ISET Bizerte

Presented on the 9th of November 2024 at Hammamet

1. Context & Motivations
2. Train a Neural Network
3. Numerical Experiments
4. In Closing

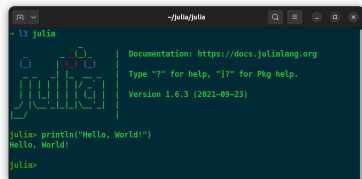
Context & Motivations

Artificial Neural Network From Scratch In Julia



Why?

- ① understanding the architecture of ANN;
- ② grasp the mathematical foundations of ANN;
- ③ develop a practical tool for learning ANN;
- ④ tweaking: loss, activation functions, optimizers, etc.

A screenshot of a terminal window titled "~julia/julia". The prompt is "+ julia". To the right of the prompt, there is a small diagram of a neural network with four layers of nodes (4, 3, 3, 2 nodes respectively) connected by lines. Further right, the text "Documentation: https://docs.julialang.org" is displayed. Below that, it says "Type '?' for help, ']' for pkg help." and "Version 1.6.3 (2021-09-23)". The user has entered the command "println(\"Hello, World!\")" and the output "Hello, World!" is shown. The prompt "julia>" is visible at the bottom.



▲ \$ docker compose up

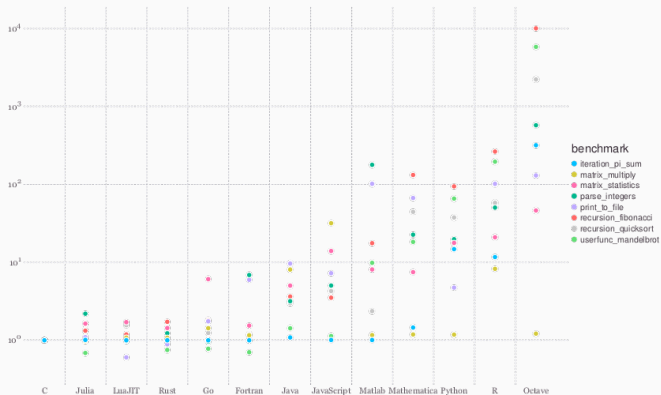
▼ \$ docker compose down



- ▲ Fast
- ▲ Dynamic
- ▲ Reproducible
- ▲ Composable
- ▲ General
- ▲ Open Source



Julia Micro-Benchmarks (1/2)



<https://julialang.org/benchmarks>

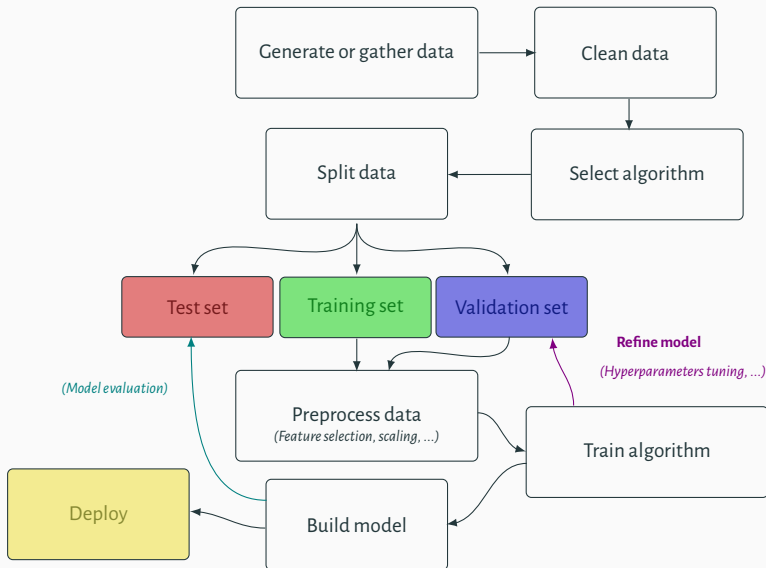


Geometric Means of Micro-Benchmarks by Language

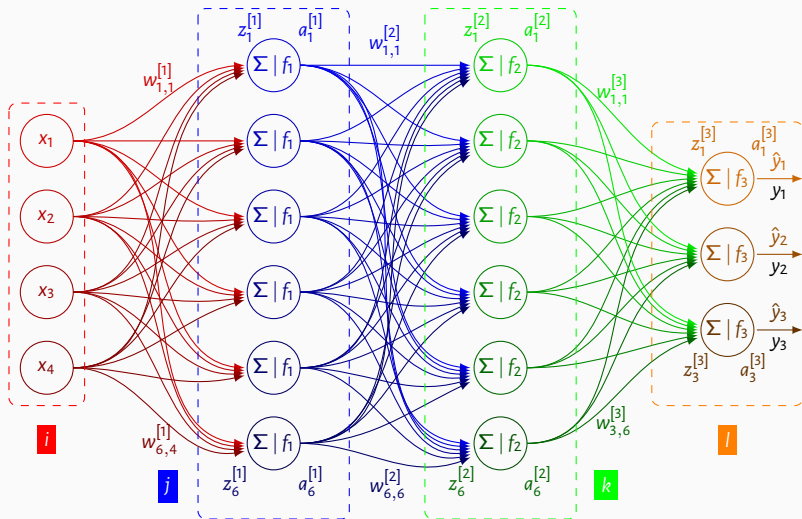
1	C	1.0
2	Julia	1.17006
3	LuaJIT	1.02931
4	Rust	1.0999
5	Go	1.49917
6	Fortran	1.67022
7	Java	3.46773
8	JavaScript	4.79602
9	Matlab	9.57235
10	Mathematica	14.6387
11	Python	16.9262
12	R	48.5796
13	Octave	338.704



Train a Neural Network



- Layer Struct
- Activation Function
- Loss Function
- Regularization
- Optimizer
- Forward and backward propagation



Multivariate chain rule

Output layer \rightarrow hidden layer #2

$$\frac{\partial \hat{y}_l}{\partial w_{l,k}^{[3]}} = \underbrace{\frac{\partial \hat{y}_l}{\partial z_l^{[3]}}}_{\dot{f}_3(z_l^{[3]})} \underbrace{\frac{\partial z_l^{[3]}}{\partial w_{l,k}^{[3]}}}_{a_k^{[2]}}$$

Output layer \rightarrow hidden layer #1

$$\frac{\partial \hat{y}_l}{\partial w_{k,j}^{[2]}} = \underbrace{\frac{\partial \hat{y}_l}{\partial z_l^{[3]}}}_{\dot{f}_3(z_l^{[3]})} \underbrace{\frac{\partial z_l^{[3]}}{\partial a_k^{[2]}}}_{w_{l,k}^{[3]}} \underbrace{\frac{\partial a_k^{[2]}}{\partial z_k^{[2]}}}_{\dot{f}_2(z_k^{[2]})} \underbrace{\frac{\partial z_k^{[2]}}{\partial w_{k,j}^{[2]}}}_{a_j^{[1]}}$$

Output layer \rightarrow input layer

$$\frac{\partial \hat{y}_l}{\partial w_{j,i}^{[1]}} = \underbrace{\frac{\partial \hat{y}_l}{\partial z_l^{[3]}}}_{\dot{f}_3(z_l^{[3]})} \underbrace{\frac{\partial z_l^{[3]}}{\partial a_k^{[2]}}}_{w_{l,k}^{[3]}} \underbrace{\frac{\partial a_k^{[2]}}{\partial z_k^{[2]}}}_{\dot{f}_2(z_k^{[2]})} \underbrace{\frac{\partial z_k^{[2]}}{\partial a_j^{[1]}}}_{w_{k,j}^{[2]}} \underbrace{\frac{\partial a_j^{[1]}}{\partial z_j^{[1]}}}_{\dot{f}_1(z_j^{[1]})} \underbrace{\frac{\partial z_j^{[1]}}{\partial w_{j,i}^{[1]}}}_{x_i}$$

Here is a list of some optimizers for artificial neural networks:

$$\Delta \hat{\mathcal{W}} \triangleq \mathcal{F} \left(\underbrace{\nabla \mathcal{J}(\hat{\mathcal{W}})}_{\text{Loss Function}} \right) \equiv \hat{\mathcal{W}} \triangleq \hat{\mathcal{W}} + \mathcal{F}(\nabla \mathcal{J}(\hat{\mathcal{W}}))$$

$$\nabla \mathcal{J}(\hat{\mathcal{W}}) = \begin{bmatrix} \frac{\partial \mathcal{J}}{\partial \hat{\mathcal{W}}_0} \\ \vdots \\ \frac{\partial \mathcal{J}}{\partial \hat{\mathcal{W}}_n} \end{bmatrix}$$

Stochastic Gradient Descent (SGD)

$$\hat{\mathcal{W}} \triangleq \hat{\mathcal{W}} - \eta \nabla \mathcal{J}(\hat{\mathcal{W}})$$

Mini-batch Gradient Descent

$$\hat{\mathcal{W}} \triangleq \hat{\mathcal{W}} - \frac{\eta}{m} \nabla \sum_{i=1}^m \mathcal{J}(\hat{\mathcal{W}}) \quad \longleftarrow m \text{ denotes the size of the mini-batch}$$

```
1  if (isa(reg.method, Symbol) && reg.method == :l1) \  
2      || (isa(reg.method, String) && lowercase(reg.method) == "l1") # LASSO  
3      for (ix, l) in enumerate(layers)  
4           $\nabla W[ix]$  .+= reg. $\lambda$  .* sign(l.W)  
5      end  
6  elseif (isa(reg.method, Symbol) && reg.method == :l2) \  
7      || (isa(reg.method, String) && lowercase(reg.method) == "l2") # RIDGE  
8      for (ix, l) in enumerate(layers)  
9           $\nabla W[ix]$  .+= reg. $\lambda$  .* l.W  
10     end  
11 elseif (isa(reg.method, Symbol) && reg.method == :elasticnet) \  
12     || (isa(reg.method, String) && lowercase(reg.method) == "elasticnet")  
13     for (ix, l) in enumerate(layers)  
14          $\nabla W[ix]$  .+= reg.r * reg. $\lambda$  .* sign(l.W) .+ (1-reg.r) * reg. $\lambda$  .* l.W  
15     end  
16 end  
17 layers[i].W -= solver. $\eta$  .*  $\nabla W[i]$   
18 layers[i].b -= solver. $\eta$  .*  $\nabla b[i]$ 
```


Numerical Experiments

```
Julia

julia> versioninfo()
Julia Version 1.10.4
Commit 48d4fd48430 (2024-06-04 10:41 UTC)
Build Info:
  Official https://julialang.org/ release
Platform Info:
  OS: Linux (x86_64-linux-gnu)
  CPU: 8 × Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz
  WORD_SIZE: 64
  LIBM: libopenlibm
  LLVM: libLLVM-15.0.7 (ORCJIT, skylake)
Threads: 1 default, 0 interactive, 1 GC (on 8 virtual cores)
Environment:
  DYLD_LIBRARY_PATH = /home/mhamdi/torch/install/lib:
  LD_LIBRARY_PATH = /home/mhamdi/torch/install/lib:

(neural-network-from-scratch...) pkg> st
Status `~/Work/git-repos/AI-ML-DL/neural-network-from-scratch-in-Julia/Project.toml`
 [91a5bccdd] Plots v1.40.5
 [ce6b1742] RDatasets v0.7.7
 [295af30f] Revise v3.5.18

(neural-network-from-scratch...) pkg> 
```

```
1  for epoch in 1:hp.epochs
2      for (data_in, data_out) in zip(data_x, data_y)
3          TrainNN(model, data_in, data_out, x_val, y_val; solver)
4      end
5      ### TRAIN LOSS
6      ŷ_train = Predict(model, x_train)
7      loss = loss_fct(y_train, ŷ_train; loss=solver.loss)
8      push!(ltn, loss)
9      ### TEST LOSS
10     ŷ_test = Predict(model, x_test)
11     loss = loss_fct(y_test, ŷ_test; loss=solver.loss)
12     push!(ltst, loss)
13 end
14 ŷ_tst = Predict(model, x_test)
15 ŷ_tst = Int.(ŷ_tst .== maximum(ŷ_tst, dims=2))
16 cm(y_test, ŷ_tst), accuracy_score(y_test, ŷ_tst), f1_score(y_test, ŷ_tst);
```



```
Julia

*** @ last *** train loss: 0.848 *** test loss: 0.850
===== EPOCH #20 =====
[ Info: loss >>> train: 0.288 *** val: 1.152
[ Info: loss >>> train: 0.360 *** val: 0.273
[ Info: loss >>> train: 0.419 *** val: 0.439
[ Info: loss >>> train: 0.369 *** val: 0.590
[ Info: loss >>> train: 0.358 *** val: 0.629
[ Info: loss >>> train: 0.363 *** val: 0.748
[ Info: loss >>> train: 0.356 *** val: 0.776
[ Info: loss >>> train: 0.354 *** val: 0.814
[ Info: loss >>> train: 0.353 *** val: 0.835
[ Info: loss >>> train: 0.352 *** val: 0.853
[ Info: loss >>> train: 0.352 *** val: 0.860
[ Info: loss >>> train: 0.352 *** val: 0.866
[ Info: loss >>> train: 0.352 *** val: 0.873
[ Info: loss >>> train: 0.352 *** val: 0.874
[ Info: loss >>> train: 0.352 *** val: 0.876
[ Info: loss >>> train: 0.352 *** val: 0.878
[ Info: loss >>> train: 0.352 *** val: 0.878
[ Info: loss >>> train: 0.352 *** val: 0.879
[ Info: loss >>> train: 0.352 *** val: 0.881
*** @ last *** train loss: 0.848 *** test loss: 0.850
Confusion Matrix
Row -> Actual & Column -> Predicted
-----
|      | (1) | (2) | (3) |
-----
| (1) | 6   | 0   | 2   |
-----
| (2) | 0   | 9   | 0   |
-----
| (3) | 3   | 0   | 10  |
-----
Accuracy = Any[0.833, 1.000, 0.833]
Precision = Any[0.667, 1.000, 0.833]
Recall = Any[0.750, 1.000, 0.769]
F1-score = [0.706, 1.000, 0.800]
([0.706, 1.000, 0.800], 0.835)

julia> 
```

In Closing

- ✓ Valuable insights into the artificial neural network architecture;
 - ✓ Practical tool for learning ANN;
 - ✓ Intuitive and easy to use.
-

- ▶ Parallelization on batch of data;
 - ▶ Optimizers: SGD-Momentum, SGD-Nesterov, RMSprop, Adam, Adagrad and Adadelta.
-

- ✓ Valuable insights into the artificial neural network architecture;
 - ✓ Practical tool for learning ANN;
 - ✓ Intuitive and easy to use.
-

- ▶ Parallelization on batch of data;
 - ▶ Optimizers: SGD-Momentum, SGD-Nesterov, RMSprop, Adam, Adagrad and Adadelta.
-

- ✓ Valuable insights into the artificial neural network architecture;
 - ✓ Practical tool for learning ANN;
 - ✓ Intuitive and easy to use.
-

- ▶ Parallelization on batch of data;
 - ▶ Optimizers: SGD-Momentum, SGD-Nesterov, RMSprop, Adam, Adagrad and Adadelta.
-



The screenshot shows the GitHub repository page for 'a-mhamdi/neural-network-from-scratch-in-Julia'. The repository is public and has 1 star and 0 forks. The 'About' section describes the project as a neural network architecture in Julia from the ground up, without using deep learning frameworks. The repository includes a README, MIT license, and activity. The file list shows the following files and their commit history:

File	Commit Message	Time
Images	add versioninfo and pkgs st to README file	3 months ago
src	fix Random.seed value and update struct	3 months ago
.gitignore	ignore folder 'SITE-CONF'	4 months ago
LICENSE	Initial commit	last year
Project.toml	RDatasets	4 months ago
README.md	fix typos and minor updates	3 months ago
main.jl	fix Random.seed value and update struct	3 months ago

<https://github.com/a-mhamdi/neural-network-from-scratch-in-Julia>

Thanks for your attention



UNDERSTANDING NEURAL NETWORKS: A FROM SCRATCH IMPLEMENTATION IN Julia

2nd International Conference on Smart Industry, Technology and Environment

Abdelbacet Mhamdi
Dr.-Ing. in EE – MT @ ISET Bizerte

Presented on the 9th of November 2024 at Hammamet