

neural network to train handwritting digits

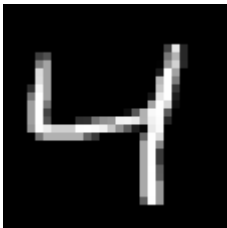
```
In [1]: import Pkg
        Pkg.add("Images")
        Pkg.add("ImageIO")
        Pkg.add("ImageMagick")
        Pkg.add("Flux")

        Updating registry at `~/.julia/registries/General`
        Resolving package versions...
        No Changes to `~/.julia/environments/v1.5/Project.toml`
        No Changes to `~/.julia/environments/v1.5/Manifest.toml`
        Resolving package versions...
        No Changes to `~/.julia/environments/v1.5/Project.toml`
        No Changes to `~/.julia/environments/v1.5/Manifest.toml`
        Resolving package versions...
        No Changes to `~/.julia/environments/v1.5/Project.toml`
        No Changes to `~/.julia/environments/v1.5/Manifest.toml`
        Resolving package versions...
        No Changes to `~/.julia/environments/v1.5/Project.toml`
        No Changes to `~/.julia/environments/v1.5/Manifest.toml`
```

```
In [2]: using Flux, Flux.Data.MNIST
        using Flux: onehotbatch, argmax, crossentropy, throttle
        using Base.Iterators: repeated
        using Images
```

```
In [3]: imgs = MNIST.images()
        colorview(Gray, imgs[3])
```

Out[3]:



```
In [4]: typeof(imgs[3])
```

Out[4]: Array{Gray{Normed{UInt8,8}},2}

First we will transform the gray scale value to float32 types. Here, using float32 will speedup the neural network substantially without compromising the quality of the solution

```
In [5]: myFloat32(x) = Float32.(x)
        fpt_imgs = myFloat32.(imgs)
        #float.(imgs)
```

```
Out[5]: 60000-element Array{Array{Float32,2},1}:
 [0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
 0.0]
 [0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
 0.0]
 [0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
 0.0]
 [0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
 0.0]
 [0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
 0.0]
 [0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
 0.0]
```

```
In [6]: sizeof(fpt_imgs[3])
```

now we will create some function to ease the solution

[illegible]

```
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
⋮
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 ... 0.0, 0.0, 0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0]
```

```
In [8]: typeof(vectorized_imgs)
```

```
Out[8]: Array{Array{Float32,1},1}
```

we will use ... as the splat operator to concatenate all images into one matrix

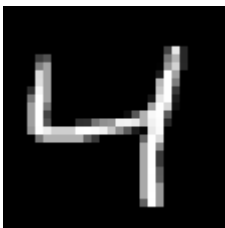
```
In [9]: X = hcat(vectorized_imgs...)
        size(X)
```

```
Out[9]: (784, 60000)
```

now every column in X is an image of a number. We have 60,000 images. when reshaped into a 28-by-28 matrix, and displayed as an image, can be seen as a handwritten number. here is an example below.

```
In [10]: onefigure = X[:,3]
         t1 = reshape(onefigure,28,28)
         colorview(Gray, t1)
```

```
Out[10]:
```



Next we will obtain the labels. These are the labels for the 60,000 images.

```
In [11]: labels = MNIST.labels()
```

```
Out[11]: 60000-element Array{Int64,1}:
```

50419221314353:789295183568

form these labels we will create a new output column for each image. These column will be the correct labels.

for example if the figure corresponding to column $X[:,i]$ is a 3, the i -th column in this new matrix Y is $[0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0]$. it is the entry numbr 4 because the entry number 1 is equal to zero. the `onehotbatch` function allows us to create this easily.

```
In [12]: Y = onehotbatch(labels, 0:9)
```

```
Out[12]: 10x60000 Flux.OneHotMatrix{Array{Flux.OneHotVector,1}}:
 0 1 0 0 0 0 0 0 0 0 0 0 0 ... 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 1 0 0 1 0 1 0 0 0 0 ... 0 0 0 0 0 0 1 0 0 0 0 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 ... 0 0 0 1 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 1 0 0 1 0 1 ... 0 0 0 0 0 0 0 1 0 0 0 0
 0 0 1 0 0 0 0 0 0 1 0 0 0 ... 0 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 0 0 0 0 1 0 ... 0 0 0 0 0 1 0 0 0 1 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 ... 0 0 0 0 0 0 0 0 0 1 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 ... 1 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 ... 0 1 0 0 0 0 0 1 0 0 0 1
 0 0 0 0 1 0 0 0 0 0 0 0 0 ... 0 0 1 0 1 0 0 0 0 0 0 0
```

And now we will actually build our neural network. we will use three layers. the hidden layer will be 32 nodes, and the output layer will have 10 nodes. will go from: $28 \times 28 \rightarrow 32 \rightarrow 10$

```
In [13]: m = Chain(
          Dense(28^2, 32, relu),
          Dense(32, 10),
          softmax)
```

```
Out[13]: Chain(Dense(784, 32, relu), Dense(32, 10), softmax)
```

what does 'm', the neural network mean have?

if you have worked with neural networks before you know that the solution is often by just one pass on the neural network. One pass happens, and a solution is generated at the output layer, then this solution is compared to the ground truth solution we already have. and the network goes back and adjusts its weights and parameters and then try again. Here since 'm' is not

trained yet, one pass of 'm' on a figure generates the following answer. we will see later how this changes after training.

```
In [14]: m(onefigure)
```

```
Out[14]: 10-element Array{Float32,1}:
 0.06901148
 0.06000702
 0.15790433
 0.10518313
 0.10149995
 0.083376884
 0.10419314
 0.10413128
 0.06747881
 0.1472139
```

to run our neural network, we need a loss function and an accuracy function. the accuracy function is used to compare the output result from the output layer in the neural network to the ground truth result. the loss function is used to evaluate the performance of the overall model after the new weights have been recalculated at each pass.

```
In [15]: loss(X, Y) = Flux.crossentropy(m(X), Y)
accuracy(X, Y) = mean(argmax(m(X)) .== argmax(Y))
```

```
Out[15]: accuracy (generic function with 1 method)
```

finally we will repeat our data so that we have more samples to pass to the neural network, which means there will be more chances for corrections.

```
In [16]: datasetx = repeated((X,Y), 200)
         C = collect(datasetx)
```

```
Out[16]: 200-element Array{Tuple{Array{Float32,2}, Flux.OneHotMatrix{Array{Flux.OneHotVector,1}}},1}:  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ⋮  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0  
 0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])  
 ([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
```

```

0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])
([0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0 0.0; ... ; 0.0 0.0 ... 0.0 0.0; 0.0 0.0 ... 0.0
0.0], [0 1 ... 0 0; 0 0 ... 0 0; ... ; 0 0 ... 0 1; 0 0 ... 0 0])

```

```
In [17]: evalcb = () -> @show(loss(X, Y))
```

```
Out[17]: #1 (generic function with 1 method)
```

```
In [18]: ps = Flux.params(m)
```

```
Out[18]: Params([Float32[0.06270066 0.07496548 ... 0.020748373 -0.06572232; -0.015000029
5 -0.04438345 ... 0.070805214 0.02018818; ... ; -0.008865638 -0.000650617 ... 0.060
5589 -0.054884747; 0.080743745 -0.06562768 ... -0.07680098 0.049419783], Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], Float32[-0.23760861 -0.18079972 ... 0.08891136 -0.25947505; -0.3175486 -0.19353496 ... -0.29015744 -0.32801253; ... ; 0.18351233 0.23587896 ... -0.016974367 0.14987819; -0.007534591 0.0723571 ... 0.059970703 0.14808933], Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0])
```

finally we are ready to train the model, we will use the Flux.train!.

for each datapoint 'd' in data compute the gradient of loss(d...) through backpropagation and call the optimiser opt.

in case datapoint 'd' are of numeric array type, assume no splatting is needed and compute the gradient of loss(d).

a callback is given with the keyword argument cb. for example this will print "training" every 10 seconds(using Flux.throttle)

```
train(loss, params, data, opt, cb = throttle(() -> println("training"), 10))
```

the callback can call Flux.stop to interrupt the training loop.

multiple optimiser and callbacks can be passed to opt and cb as arrays.

```
In [19]: opt = ADAM()
Flux.train!(loss, ps, datasetx, opt, cb = throttle(evalcb, 10))
```

```

loss(X, Y) = 2.3134577f0
loss(X, Y) = 1.1963089f0
loss(X, Y) = 0.6820752f0
loss(X, Y) = 0.4822105f0
loss(X, Y) = 0.39453807f0
loss(X, Y) = 0.3464755f0
loss(X, Y) = 0.31494108f0

```

```
loss(X, Y) = 0.29414213f0
loss(X, Y) = 0.27677095f0
```

we will now get the test data.

```
In [20]: tX = hcat(float.(reshape.(MNIST.images(:test), :))...)
         test_image = m(tX[:, 1])
```

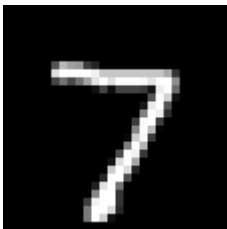
```
Out[20]: 10-element Array{Float32,1}:
          0.000119618744
          6.090899f-7
          0.00056266884
          0.0025706952
          1.6129106f-5
          7.0131835f-5
          1.7056531f-6
          0.9952661
          0.00012234825
          0.0012700767
```

```
In [21]: argmax(test_image) - 1
```

```
Out[21]: 7
```

```
In [22]: t1 = reshape(tX[:,1],28,28)
         colorview(Gray, t1)
```

```
Out[22]:
```



what about the image we tried a few cells earlier and returned the "not-so-great" answer.

```
In [23]: onefigure = X[:,3]
         m(onefigure)
```

```
Out[23]: 10-element Array{Float32,1}:
          0.0010987261
          0.00022808085
          0.03906273
          0.0617313
          0.7957977
          0.0007101971
          0.000191614
          0.014489284
          0.0010007302
          0.08568969
```

you can see that the argmax is [0 0 0 1 0 0 0 0 0]

```
In [24]: Y[:,3]
```

```
Out[24]: 10-element Flux.OneHotVector:
          0
          0
          0
          0
          1
          0
          0
          0
          0
          0
```

and the number is 4 too, it predicted true.

In []: