

Learning MNIST with Neural Networks with backprop library

Justin Le

The *backprop* library performs back-propagation over a *heterogeneous* system of relationships. It offers both an implicit (*ad*¹-like) and explicit graph building usage style. Let's use it to build neural networks and learn mnist!

Repository source is on github², and docs are on hackage³.

If you're reading this as a literate haskell file, you should know that a rendered pdf version is available on github.⁴ If you are reading this as a pdf file, you should know that a literate haskell version that you can run⁵ is also available on github!

```
{-# LANGUAGE BangPatterns           #-}
{-# LANGUAGE DataKinds             #-}
{-# LANGUAGE DeriveGeneric         #-}
{-# LANGUAGE GADTs                 #-}
{-# LANGUAGE LambdaCase           #-}
{-# LANGUAGE ScopedTypeVariables   #-}
{-# LANGUAGE TupleSections         #-}
{-# LANGUAGE TypeApplications     #-}
{-# LANGUAGE ViewPatterns         #-}
{-# OPTIONS_GHC -fno-warn-orphans   #-}
{-# OPTIONS_GHC -fno-warn-incomplete-patterns #-}
{-# OPTIONS_GHC -fno-warn-unused-top-binds #-}

import Control.DeepSeq
import Control.Exception
import Control.Monad
import Control.Monad.IO.Class
import Control.Monad.Trans.Maybe
import Control.Monad.Trans.State
import Data.Bitraversable
import Data.Foldable
import Data.IDX
import Data.List.Split
import Data.Maybe
import Data.Time.Clock
import Data.Traversable
import Data.Tuple
import GHC.Generics (Generic)
```

¹<http://hackage.haskell.org/package/ad>

²<https://github.com/mstksg/backprop>

³<http://hackage.haskell.org/package/backprop>

⁴<https://github.com/mstksg/backprop/blob/master/renders/MNIST.pdf>

⁵<https://github.com/mstksg/backprop/blob/master/samples/MNIST.lhs>

```

import      GHC.TypeLits
import      Numeric.Backprop
import      Numeric.LinearAlgebra.Static hiding (dot)
import      Text.Printf
import qualified Data.Vector           as V
import qualified Data.Vector.Generic   as VG
import qualified Data.Vector.Unboxed   as VU
import qualified Generics.SOP          as SOP
import qualified Numeric.LinearAlgebra as HM
import qualified System.Random.MWC     as MWC
import qualified System.Random.MWC.Distributions as MWC

```

Types

For the most part, we're going to be using the great *hmatrix*⁶ library and its vector and matrix types. It offers a type $L\ m\ n$ for $m \times n$ matrices, and a type $R\ n$ for an n vector.

First things first: let's define our neural networks as simple containers of parameters (weight matrices and bias vectors).

First, a type for layers:

```

data Layer i o =
  Layer { _lWeights :: !(L o i)
        , _lBiases  :: !(R o)
        }
  deriving (Show, Generic)

instance SOP.Generic (Layer i o)
instance NFData (Layer i o)

```

And a type for a simple feed-forward network with two hidden layers:

```

data Network i h1 h2 o =
  Net { _nLayer1 :: !(Layer i h1)
      , _nLayer2 :: !(Layer h1 h2)
      , _nLayer3 :: !(Layer h2 o)
      }
  deriving (Show, Generic)

instance SOP.Generic (Network i h1 h2 o)
instance NFData (Network i h1 h2 o)

```

These are pretty straightforward container types... pretty much exactly the type you'd make to represent these networks! Note that, following true Haskell form, we separate out logic from data. This should be all we need.

We derive an instance of `SOP.Generic` from the *generics-sop*⁷ package, which *backprop* uses to propagate derivatives on values inside product types.

⁶<http://hackage.haskell.org/package/hmatrix>

⁷<http://hackage.haskell.org/package/generics-sop>

Instances

Things are much simpler if we had `Num` and `Fractional` instances for everything, so let's just go ahead and define that now, as well. Just a little bit of boilerplate.

```
instance (KnownNat i, KnownNat o) => Num (Layer i o) where
  Layer w1 b1 + Layer w2 b2 = Layer (w1 + w2) (b1 + b2)
  Layer w1 b1 - Layer w2 b2 = Layer (w1 - w2) (b1 - b2)
  Layer w1 b1 * Layer w2 b2 = Layer (w1 * w2) (b1 * b2)
  abs (Layer w b)           = Layer (abs w) (abs b)
  signum (Layer w b)       = Layer (signum w) (signum b)
  negate (Layer w b)       = Layer (negate w) (negate b)
  fromInteger x            = Layer (fromInteger x) (fromInteger x)

instance (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o) => Num (Network i h1 h2 o) where
  Net a b c + Net d e f = Net (a + d) (b + e) (c + f)
  Net a b c - Net d e f = Net (a - d) (b - e) (c - f)
  Net a b c * Net d e f = Net (a * d) (b * e) (c * f)
  abs (Net a b c)       = Net (abs a) (abs b) (abs c)
  signum (Net a b c)    = Net (signum a) (signum b) (signum c)
  negate (Net a b c)    = Net (negate a) (negate b) (negate c)
  fromInteger x         = Net (fromInteger x) (fromInteger x) (fromInteger x)

instance (KnownNat i, KnownNat o) => Fractional (Layer i o) where
  Layer w1 b1 / Layer w2 b2 = Layer (w1 / w2) (b1 / b2)
  recip (Layer w b)         = Layer (recip w) (recip b)
  fromRational x            = Layer (fromRational x) (fromRational x)

instance (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o) => Fractional (Network i h1 h2 o) where
  Net a b c / Net d e f = Net (a / d) (b / e) (c / f)
  recip (Net a b c)     = Net (recip a) (recip b) (recip c)
  fromRational x        = Net (fromRational x) (fromRational x) (fromRational x)
```

`KnownNat` comes from *base*; it's a typeclass that *hmatrix* uses to refer to the numbers in its type and use it to go about its normal *hmatrix* business.

Ops

Now, *backprop* does require *primitive* differentiable operations on our relevant types to be defined. *backprop* uses these primitive `Ops` to tie everything together. Ideally we'd import these from a library that implements these for you, and the end-user never has to make `Op` primitives.

But in this case, I'm going to put the definitions here to show that there isn't any magic going on. If you're curious, refer to documentation for `Op`⁸ for more details on how `Op` is implemented and how this works.

First, matrix-vector multiplication primitive, giving an explicit gradient function.

```
matVec
  :: (KnownNat m, KnownNat n)
  => Op '[ L m n, R n ] (R m)
matVec = op2' $ \m v ->
  ( m #> v, \ (fromMaybe 1 -> g) ->
```

⁸<http://hackage.haskell.org/package/backprop/docs/Numeric-Backprop-Op.html>

```
)
      (g `outer` v, tr m #> g)
)
```

Dot products would be nice too.

```
dot :: KnownNat n
     => Op '[ R n, R n ] Double
dot = op2' $ \x y ->
  ( x <.> y, \case Nothing -> (y, x)
                    Just g  -> (konst g * y, x * konst g)
  )
```

Also a “scaling” function, scales a vector by a given factor.

```
scale
  :: KnownNat n
  => Op '[ Double, R n ] (R n)
scale = op2' $ \a x ->
  ( konst a * x
  , \case Nothing -> (HM.sumElements (extract x      ), konst a      )
    Just g  -> (HM.sumElements (extract (x * g)), konst a * g)
  )
```

Finally, an operation to sum all of the items in the vector.

```
vsum
  :: KnownNat n
  => Op '[ R n ] Double
vsum = op1' $ \x -> (HM.sumElements (extract x), maybe 1 konst)
```

And why not, here’s the logistic function⁹, which we’ll use as an activation function for internal layers. We don’t need to define this as an `Op` up-front right now, because the library can automatically promote any numeric polymorphic function (an `a -> a` or `a -> a -> a`, etc.) to an `Op` anyways.

```
logistic :: Floating a => a -> a
logistic x = 1 / (1 + exp (-x))
```

Running our Network

Now that we have our primitives in place, let’s actually write a function to run our network!

```
runLayer
  :: (KnownNat i, KnownNat o)
  => BPOp s '[ R i, Layer i o ] (R o)
runLayer = withInps $ \ (x :< l :< ∅) -> do
  w :< b :< ∅ <- gTuple #<~ l
  y <- matVec ~$ (w :< x :< ∅)
  return $ y + b
```

`ABPOp s '[R i, Layer i o] (R o)` is a backpropagatable function that produces an `R o` (a vector with `o` elements, from the *hmatrix*¹⁰ library) given an input environment of an `R i` (the “input” of the layer) and a layer.

⁹https://en.wikipedia.org/wiki/Logistic_function

¹⁰<http://hackage.haskell.org/package/hmatrix>

We use `withInps` to bring the environment into scope as a bunch of `BVars`. `x` is a `BVar` containing the input vector, and `l` is a `BVar` containing the layer.

The first thing we do is split out the parts of the layer so we can work with the internal matrices. We can use `#<~` to “split out” the components of a `BVar`, splitting on `gTuple` (which uses `GHC.Generics` to automatically figure out how to split up a product type).

Then we apply `matVec` (our primitive `Op` that does matrix-vector multiplication) to `w` and `x`, and then the result is that added to the bias vector `b`.

We can write the `runNetwork` function pretty much the same way.

```
runNetwork
  :: (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o)
  => BPOp s '[ R i, Network i h1 h2 o ] (R o)
runNetwork = withInps $ \(x :< n :< ∅) -> do
  l1 :< l2 :< l3 :< ∅ <- gTuple #<~ n
  y <- runLayer -$ (x :< l1 :< ∅)
  z <- runLayer -$ (logistic y :< l2 :< ∅)
  r <- runLayer -$ (logistic z :< l3 :< ∅)
  softmax -$ (r :< ∅)
where
  softmax :: KnownNat n => BPOp s '[ R n ] (R n)
  softmax = withInps $ \(x :< ∅) -> do
    expX <- bindVar (exp x)
    totX <- vsum ~$ (expX :< ∅)
    scale ~$ (1/totX :< expX :< ∅)
```

After splitting out the layers in the input `Network`, we run each layer successively using our previously defined `runLayer`, giving inputs using `-$`. We can directly apply `logistic` to `BVars`. At the end, we run a softmax function¹¹ because MNIST is a classification challenge. The softmax is done by applying e^x for every item in the input vector, and dividing each element by the total.

The Magic

What did we just define? Well, with a `BPOp s rs a`, we can *run* it and get the output:

```
runNetOnInp
  :: (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o)
  => Network i h1 h2 o
  -> R i
  -> R o
runNetOnInp n x = evalBPOp runNetwork (x ::< n ::< ∅)
```

But, the magic part is that we can also get the gradient!

```
gradNet
  :: (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o)
  => Network i h1 h2 o
  -> R i
  -> Network i h1 h2 o
gradNet n x = case gradBPOp runNetwork (x ::< n ::< ∅) of
  _gradX ::< gradN ::< ∅ -> gradN
```

This gives the gradient of all of the parameters in the matrices and vectors inside the `Network`, which we can use to “train”!

¹¹https://en.wikipedia.org/wiki/Softmax_function

Training

Now for the real work. To train a network, we can do gradient descent based on the gradient of some type of *error function* with respect to the network parameters. Let's use the cross entropy¹², which is popular for classification problems.

```
crossEntropy
  :: KnownNat n
  => R n
  -> BPOpI s '[ R n ] Double
crossEntropy targ (r :< ∅) = negate (dot .$ (log r :< t :< ∅))
  where
    t = constVar targ
```

Given a target vector and a BVar referring to the result of the network, we can directly apply:

$$H(\mathbf{r}, \mathbf{t}) = -(\log(\mathbf{r}) \cdot \mathbf{t})$$

Just for fun, I implemented `crossEntropy` in “implicit-graph” mode, so you don't see any binds or returns.

Now, a function to make one gradient descent step based on an input vector and a target, using `gradBPOp`:

```
trainStep
  :: forall i h1 h2 o. (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o)
  => Double
  -> R i
  -> R o
  -> Network i h1 h2 o
  -> Network i h1 h2 o
trainStep r !x !t !n = case gradBPOp o (x ::< n ::< ∅) of
  _ ::< gN ::< ∅ ->
    n - (realToFrac r * gN)
  where
    o :: BPOp s '[ R i, Network i h1 h2 o ] Double
    o = do
      y <- runNetwork
      implicitly (crossEntropy t) -$ (y :< ∅)
```

A convenient wrapper for training over all of the observations in a list:

```
trainList
  :: (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o)
  => Double
  -> [(R i, R o)]
  -> Network i h1 h2 o
  -> Network i h1 h2 o
trainList r = flip $ foldl' (\n (x,y) -> trainStep r x y n)
```

Pulling it all together

`testNet` will be a quick way to test our net by computing the percentage of correct guesses: (mostly using *hmatrix* stuff)

¹²https://en.wikipedia.org/wiki/Cross_entropy

```

testNet
  :: forall i h1 h2 o. (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o)
  => [(R i, R o)]
  -> Network i h1 h2 o
  -> Double
testNet xs n = sum (map (uncurry test) xs) / fromIntegral (length xs)
where
  test :: R i -> R o -> Double
  test x (extract->t)
    | HM.maxIndex t == HM.maxIndex (extract r) = 1
    | otherwise                               = 0
  where
    r :: R o
    r = evalBPOp runNetwork (x ::< n ::< ∅)

```

And now, a main loop!

If you are following along at home, download the mnist data set files¹³ and uncompress them into the folder data, and everything should work fine.

```

main :: IO ()
main = MWC.withSystemRandom $ \g -> do
  Just train <- loadMNIST "data/train-images-idx3-ubyte" "data/train-labels-idx1-ubyte"
  Just test  <- loadMNIST "data/t10k-images-idx3-ubyte" "data/t10k-labels-idx1-ubyte"
  putStrLn "Loaded data."
  net0 <- MWC.uniformR @(Network 784 300 100 9) (-0.5, 0.5) g
  flip evalStateT net0 . forM_ [1..] $ \e -> do
    train' <- liftIO . fmap V.toList $ MWC.uniformShuffle (V.fromList train) g
    liftIO $ printf "[Epoch %d]\n" (e :: Int)

    forM_ ([1..] `zip` chunksOf batch train') $ \(b, chnk) -> StateT $ \n0 -> do
      printf "(Batch %d)\n" (b :: Int)

      t0 <- getCurrentTime
      n' <- evaluate . force $ trainList rate chnk n0
      t1 <- getCurrentTime
      printf "Trained on %d points in %s.\n" batch (show (t1 `diffUTCTime` t0))

      let trainScore = testNet chnk n'
          testScore  = testNet test n'
          printf "Training error:  %.2f%%\n" ((1 - trainScore) * 100)
          printf "Validation error: %.2f%%\n" ((1 - testScore) * 100)

      return ((), n')

  where
    rate  = 0.02
    batch = 5000

```

Each iteration of the loop:

1. Shuffles the training set
2. Splits it into chunks of batch size
3. Uses `trainList` to train over the batch
4. Computes the score based on `testNet` based on the training set and the test set

¹³<http://yann.lecun.com/exdb/mnist/>

5. Prints out the results

And, that's really it!

Result

I haven't put much into optimizing the library yet, but the network (with hidden layer sizes 300 and 100) seems to take 25s on my computer to finish a batch of 5000 training points. It's slow (five minutes per 60000 point epoch), but it's a first unoptimized run and a proof of concept! It's my goal to get this down to a point where the result has the same performance characteristics as the actual backend (*hmatrix*), and so overhead is 0.

Main takeaways

Most of the actual heavy lifting/logic actually came from the *hmatrix* library itself. We just created simple types to wrap up our bare matrices.

Basically, all that *backprop* did was give you an API to define *how to run* a neural net — how to *run* a net based on a `Network` and `R i` input you were given. The goal of the library is to let you write down how to run things in as natural way as possible.

And then, after things are run, we can just get the gradient and roll from there!

Because the heavy lifting is done by the data types themselves, we can presumably plug in *any* type and any tensor/numerical backend, and reap the benefits of those libraries' optimizations and parallelizations. *Any* type can be backpropagated! :D

What now?

Check out the docs for the `Numeric.Backprop`¹⁴ module for a more detailed picture of what's going on, or find more examples at the github repo¹⁵!

Boring stuff

Here is a small wrapper function over the `mnist-idx`¹⁶ library loading the contents of the `idx` files into *hmatrix* vectors:

```
loadMNIST
  :: FilePath
  -> FilePath
  -> IO (Maybe [(R 784, R 9)])
loadMNIST fpI fpL = runMaybeT $ do
  i <- MaybeT $ decodeIDXFile fpI
  l <- MaybeT $ decodeIDXLabelsFile fpL
  d <- MaybeT . return $ labeledIntData l i
  r <- MaybeT . return $ for d (bitraverse mkImage mkLabel . swap)
  liftIO . evaluate $ force r
where
```

¹⁴<http://hackage.haskell.org/package/backprop/docs/Numeric-Backprop.html>

¹⁵<https://github.com/mstksg/backprop>

¹⁶<http://hackage.haskell.org/package/mnist-idx>


```

mkImage :: VU.Vector Int -> Maybe (R 784)
mkImage = create . VG.convert . VG.map (\i -> fromIntegral i / 255)
mkLabel :: Int -> Maybe (R 9)
mkLabel n = create $ HM.build 9 (\i -> if round i == n then 1 else 0)

```

And here are instances to generating random vectors/matrices/layers/networks, used for the initialization step.

```

instance KnownNat n => MWC.Variate (R n) where
  uniform g = randomVector <$> MWC.uniform g <*> pure Uniform
  uniformR (l, h) g = (\x -> x * (h - l) + l) <$> MWC.uniform g

instance (KnownNat m, KnownNat n) => MWC.Variate (L m n) where
  uniform g = uniformSample <$> MWC.uniform g <*> pure 0 <*> pure 1
  uniformR (l, h) g = (\x -> x * (h - l) + l) <$> MWC.uniform g

instance (KnownNat i, KnownNat o) => MWC.Variate (Layer i o) where
  uniform g = Layer <$> MWC.uniform g <*> MWC.uniform g
  uniformR (l, h) g = (\x -> x * (h - l) + l) <$> MWC.uniform g

instance (KnownNat i, KnownNat h1, KnownNat h2, KnownNat o) => MWC.Variate (Network i h1 h2 o) where
  uniform g = Net <$> MWC.uniform g <*> MWC.uniform g <*> MWC.uniform g
  uniformR (l, h) g = (\x -> x * (h - l) + l) <$> MWC.uniform g

```