

Practical Dependent Types: Type-Safe Neural Networks

Justin Le <https://blog.jle.im> (justin@je.im)

Lambdaconf 2017, May 27, 2017

Preface

Slide available at <https://talks.jle.im/lambdaconf-2017/dependent-types/dependent-types.html>.

All code available at
<https://github.com/mstksg/talks/tree/master/lambdaconf-2017/dependent-types>.

Libraries required: (available on Hackage) *hmatrix*, *singletons*, *MonadRandom*. GHC 8.x assumed.

The Big Question

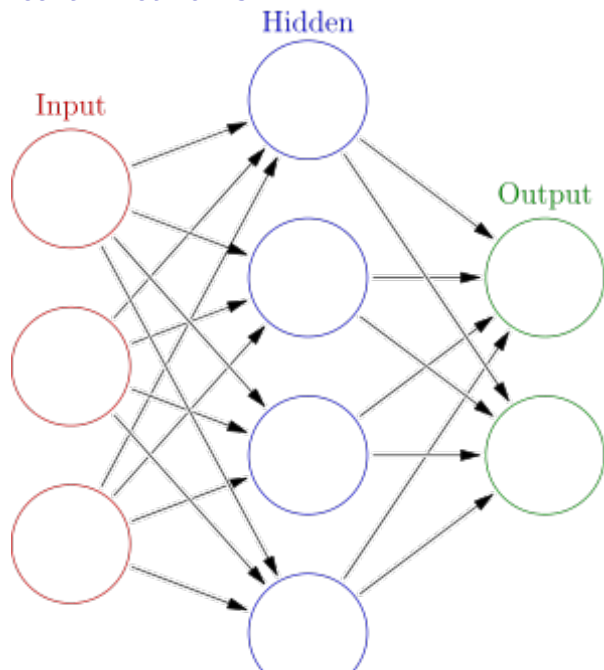
The big question of Haskell: *What can types do for us?*

The Big Question

The big question of Haskell: *What can types do for us?*

Dependent types are simply the extension of this question, pushing the power of types further.

Artificial Neural Networks



Parameterized functions

Each layer receives an input vector, $\mathbf{x} : \mathbb{R}^n$, and produces an output $\mathbf{y} : \mathbb{R}^m$.

Parameterized functions

Each layer receives an input vector, $\mathbf{x} : \mathbb{R}^n$, and produces an output $\mathbf{y} : \mathbb{R}^m$.

They are parameterized by a weight matrix $W : \mathbb{R}^{m \times n}$ (an $m \times n$ matrix) and a bias vector $\mathbf{b} : \mathbb{R}^m$, and the result is: (for some activation function f)

$$\mathbf{y} = f(W\mathbf{x} + \mathbf{b})$$

A neural network would take a vector through many layers.

Networks in Haskell

```
data Weights = W { wBiases :: !(Vector Double)  -- n
                  , wNodes  :: !(Matrix Double) -- n x m
                  }                               -- "m to n"
```

```
data Network :: Type where
    0      :: !Weights -> Network
    (:~)  :: !Weights -> !Network -> Network
infixr 5 :~
```


Networks in Haskell

```
data Weights = W { wBiases :: !(Vector Double)  -- n
                  , wNodes  :: !(Matrix Double)  -- n x m
                  }                               -- "m to n"
```

```
data Network :: Type where
    0      :: !Weights -> Network
    (:~)  :: !Weights -> !Network -> Network
infixr 5 :~
```

A network with one input layer, two hidden layers, and one output layer would be:

```
h1 :~ h2 :~ 0 o
```

Running them

```
runLayer :: Weights -> Vector Double -> Vector Double
```

```
runLayer (W wB wN) v = wB + wN #> v
```

```
runNet :: Network -> Vector Double -> Vector Double
```

```
runNet (O w) !v = logistic (runLayer w v)
```

```
runNet (w :~ n') !v = let v' = logistic (runLayer w v)
                      in runNet n' v'
```

Generating them

```
randomWeights :: MonadRandom m => Int -> Int -> m Weights
randomWeights i o = do
  seed1 :: Int <- getRandom
  seed2 :: Int <- getRandom
  let wB = randomVector seed1 Uniform o * 2 - 1
      wN = uniformSample seed2 o (replicate i (-1, 1))
  return $ W wB wN

randomNet :: MonadRandom m => Int -> [Int] -> Int -> m Net
randomNet i [] o = 0 <$> randomWeights i o
randomNet i (h:hs) o = (:~) <$> randomWeights i h <*> randomNet i hs o
```

Haskell Heart Attacks

- ▶ What if we mixed up the dimensions for `randomWeights`?

Haskell Heart Attacks

- ▶ What if we mixed up the dimensions for `randomWeights`?
- ▶ What if the *user* mixed up the dimensions for `randomWeights`?

Haskell Heart Attacks

- ▶ What if we mixed up the dimensions for `randomWeights`?
- ▶ What if the *user* mixed up the dimensions for `randomWeights`?
- ▶ What if layers in the network are incompatible?

Haskell Heart Attacks

- ▶ What if we mixed up the dimensions for `randomWeights`?
- ▶ What if the *user* mixed up the dimensions for `randomWeights`?
- ▶ What if layers in the network are incompatible?
- ▶ How does the user know what size vector a network expects?

Haskell Heart Attacks

- ▶ What if we mixed up the dimensions for `randomWeights`?
- ▶ What if the *user* mixed up the dimensions for `randomWeights`?
- ▶ What if layers in the network are incompatible?
- ▶ How does the user know what size vector a network expects?
- ▶ Is our `runLayer` and `runNet` implementation correct?

Backprop

```
train :: Double           -- ^ learning rate
      -> Vector Double    -- ^ input vector
      -> Vector Double    -- ^ target vector
      -> Network          -- ^ network to train
      -> Network

train rate x0 target = fst . go x0
  where
```

Backprop (Outer layer)

```
go :: Vector Double      -- ^ input vector
  -> Network              -- ^ network to train
  -> (Network, Vector Double)
-- handle the output layer
go !x (O w@(W wB wN))
  = let y      = runLayer w x
      o      = logistic y
          -- the gradient (how much y affects the error)
          -- (logistic' is the derivative of logistic)
      dEdy = logistic' y * (o - target)
          -- new bias weights and node weights
      wB'  = wB - scale rate dEdy
      wN'  = wN - scale rate (dEdy `outer` x)
      w'   = W wB' wN'
          -- bundle of derivatives for next step
      dWs  = tr wN #> dEdy
  in (O w', dWs)
```

Backprop (Inner layer)

```
-- handle the inner layers
go !x (w@(W wB wN) :~ n)
  = let y          = runLayer w x
      o          = logistic y
      -- get dWs', bundle of derivatives from rest
      (n', dWs') = go o n
      -- the gradient (how much y affects the error)
      dEdy       = logistic' y * dWs'
      -- new bias weights and node weights
      wB'        = wB - scale rate dEdy
      wN'        = wN - scale rate (dEdy `outer` x)
      w'         = W wB' wN'
      -- bundle of derivatives for next step
      dWs        = tr wN #> dEdy
  in (w' :~ n', dWs)
```

Compiler, O Where Art Thou?

- ▶ Haskell is all about the compiler helping guide you write your code. But how much did the compiler help there?

Compiler, O Where Art Thou?

- ▶ Haskell is all about the compiler helping guide you write your code. But how much did the compiler help there?
- ▶ How can the “shape” of the matrices guide our programming?

Compiler, O Where Art Thou?

- ▶ Haskell is all about the compiler helping guide you write your code. But how much did the compiler help there?
- ▶ How can the “shape” of the matrices guide our programming?
- ▶ We basically rely on naming conventions to make sure we write our code correctly.

Haskell Red Flags

- ▶ How many ways can we write the function and have it still typecheck?

Haskell Red Flags

- ▶ How many ways can we write the function and have it still typecheck?
- ▶ How many of our functions are partial?

A Typed Alternative

```
data Weights i o = W { wBiases :: !(R o)
                       , wNodes  :: !(L o i)
                       }
```

An $o \times i$ layer

A Typed Alternative

From HMatrix:

```
R :: Nat -> Type
```

```
L :: Nat -> Nat -> Type
```

An $R\ 3$ is a 3-vector, an $L\ 4\ 3$ is a 4×3 matrix.

A Typed Alternative

From HMatrix:

```
R :: Nat -> Type
```

```
L :: Nat -> Nat -> Type
```

An `R 3` is a 3-vector, an `L 4 3` is a 4×3 matrix.

Operations are typed:

```
(+) :: KnownNat n => R n -> R n -> R n
```

```
(<#) :: (KnownNat m, KnownNat n) => L m n -> R n -> R m
```

`KnownNat n` lets `hmatrix` use the `n` in the type. Typed holes can guide our development, too!

Data Kinds

With `-XDataKinds`, all values and types are lifted to types and kinds.

Data Kinds

With `-XDataKinds`, all values and types are lifted to types and kinds.

In addition to the values `True`, `False`, and the type `Bool`, we also have the **type** `'True`, `'False`, and the **kind** `Bool`.

In addition to `:` and `[]` and the list type, we have `':` and `'[]` and the list kind.

Data Kinds

```
ghci> :t True
```

```
Bool
```

```
ghci> :k 'True
```

```
Bool
```

```
ghci> :t [True, False]
```

```
[Bool]
```

```
ghci> :k '[ 'True, 'False ]
```

```
[Bool]
```

A Typed Alternative

```
data Network :: Nat -> [Nat] -> Nat -> Type where
  0      :: !(Weights i o)
         -> Network i '[] o
  (:~)  :: KnownNat h
         => !(Weights i h)
         -> !(Network h hs o)
         -> Network i (h ': hs) o
infixr 5 :~
```

A Typed Alternative

```
data Network :: Nat -> [Nat] -> Nat -> Type where
  0      :: !(Weights i o)
         -> Network i '[] o
  (:~)  :: KnownNat h
         => !(Weights i h)
         -> !(Network h hs o)
         -> Network i (h ': hs) o

infixr 5 :~

h1 :: Weight 10 8
h2 :: Weight 8 5
o  :: Weight 5 2

      0 o :: Network 5 '[] 2
h2 :~ 0 o :: Network 8 '[5] 2
h1 :~ h2 :~ 0 o :: Network 10 '[8, 5] 2
h2 :~ h1 :~ 0 o -- type error
```


Running

```
runLayer :: (KnownNat i, KnownNat o)
```

```
  => Weights i o
```

```
  -> R i
```

```
  -> R o
```

```
runLayer (W wB wN) v = wB + wN #> v
```

```
runNet :: (KnownNat i, KnownNat o)
```

```
  => Network i hs o
```

```
  -> R i
```

```
  -> R o
```

```
runNet (O w) !v = logistic (runLayer w v)
```

```
runNet (w :~ n') !v = let v' = logistic (runLayer w v)
```

```
  in runNet n' v'
```

Exactly the same! No loss in expressivity!

Running

Much better! Matrices and vector lengths are guaranteed to line up!

Generating

```
randomWeights :: (MonadRandom m, KnownNat i, KnownNat o)
               => m (Weights i o)
randomWeights = do
  s1 :: Int <- getRandom
  s2 :: Int <- getRandom
  let wB = randomVector s1 Uniform * 2 - 1
      wN = uniformSample s2 (-1) 1
  return $ W wB wN
```

No need for explicit arguments! User can demand `i` and `o`. No reliance on documentation and parameter orders.

Generating

But, for generating nets, we have a problem:

```
randomNet :: forall m i hs o. (MonadRandom m, KnownNat i, P
    => m (Network i hs o)
randomNet = case hs of [] -> ??
```

Pattern matching on types

The solution for pattern matching on types: singletons.

```
-- (not the actual implementation)
```

```
data Sing :: Bool -> Type where
```

```
  SFalse :: Sing 'False
```

```
  STrue  :: Sing 'True
```

```
data Sing :: [k] -> Type where
```

```
  SNil  :: Sing '[]
```

```
  SCons :: Sing x -> Sing xs -> Sing (x ': xs)
```

```
data Sing :: Nat -> Type where
```

```
  SNat :: KnownNat n => Sing n
```

Pattern matching on types

```
ghci> :t SFalse
Sing 'False
ghci> :t STrue `SCons` (SFalse `SCons` SNil)
Sing '[True, False]
ghci> :t SNat @1 `SCons` (SNat @2 `SCons` SNil)
Sing '[1, 2]
```

Random networks

```
randomNet' :: forall m i hs o. (MonadRandom m, KnownNat i,
    => Sing hs -> m (Network i hs o))
randomNet' = \case
  SNil          -> 0 <$> randomWeights
  SNat `SCons` ss -> (:~) <$> randomWeights <*> randomNet
```

Implicit passing

Explicitly passing singletons can be ugly.

Implicit passing

Explicitly passing singletons can be ugly.

```
class SingI x where  
  sing :: Sing x
```

We can now recover the expressivity of the original function, and gain demand-driven shapes.

Implicit passing

Explicitly passing singletons can be ugly.

```
class SingI x where
  sing :: Sing x
```

We can now recover the expressivity of the original function, and gain demand-driven shapes.

```
randomNet :: forall m i hs o. (MonadRandom m, KnownNat i, S
    => m (Network i hs o)
randomNet = randomNet' sing
```

Backprop

```
train :: forall i hs o. (KnownNat i, KnownNat o)
  => Double           -- ^ learning rate
  -> R i              -- ^ input vector
  -> R o              -- ^ target vector
  -> Network i hs o  -- ^ network to train
  -> Network i hs o
train rate x0 target = fst . go x0
```

Backprop

```
train :: forall i hs o. (KnownNat i, KnownNat o)
  => Double           -- ^ learning rate
  -> R i              -- ^ input vector
  -> R o              -- ^ target vector
  -> Network i hs o  -- ^ network to train
  -> Network i hs o
train rate x0 target = fst . go x0
```

Ready for this?

Backprop

```
go :: forall j js. KnownNat j
  => R j          -- ^ input vector
  -> Network j js o  -- ^ network to train
  -> (Network j js o, R j)
-- handle the output layer
go !x (O w@(W wB wN))
  = let y      = runLayer w x
        o      = logistic y
        -- the gradient (how much y affects the error)
        -- (logistic' is the derivative of logistic)
        dEdey = logistic' y * (o - target)
        -- new bias weights and node weights
        wB'    = wB - konst rate * dEdey
        wN'    = wN - konst rate * (dEdey `outer` x)
        w'     = W wB' wN'
        -- bundle of derivatives for next step
        dWs    = tr wN #> dEdey
  in (O w', dWs)
```

Backprop

```
-- handle the inner layers
go !x (w@(W wB wN) :~ n)
  = let y          = runLayer w x
      o           = logistic y
      -- get dWs', bundle of derivatives from rest
      (n', dWs') = go o n
      -- the gradient (how much y affects the error)
      dEdy       = logistic' y * dWs'
      -- new bias weights and node weights
      wB'        = wB - konst rate * dEdy
      wN'        = wN - konst rate * (dEdy `outer` x)
      w'         = W wB' wN'
      -- bundle of derivatives for next step
      dWs        = tr wN #> dEdy
  in (w' :~ n', dWs)
```

Surprise! It's actually identical! No loss in expressivity. Typed holes can write our code for us in many cases. And shapes are all verified.

Type-Driven Development

We wrote an untyped implementation, then realized what was wrong. Then we added types, and everything is great!

Further reading

- ▶ Blog series: <https://blog.jle.im/entries/series/+practical-dependent-types-in-haskell.html>
- ▶ Extra resources:
 - ▶ <https://www.youtube.com/watch?v=rhWMhTjQzsU>
 - ▶ <http://www.well-typed.com/blog/2015/11/implementing-a-minimal-version-of-haskell-servant/>
 - ▶ <https://www.schoolofhaskell.com/user/konn/prove-your-haskell-for-great-safety>
 - ▶ <http://jozefg.bitbucket.org/posts/2014-08-25-dep-types-part-1.html>