# 2-Layer Neural Network

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# 1 Preamble

```
module NeuralNetwork where

import Numeric.LinearAlgebra
import Prelude hiding ((<>))

type Vec = Vector R
type Mat = Matrix R
```

## 2 Constants

```
inputSize
             :: Int
hiddenSize :: Int
outputSize :: Int
inputSize = 784
hiddenSize = 50
outputSize = 10
w1_start
             :: Int
w1_size
             :: Int
w2_start
           :: Int
           :: Int
w2_size
b2_start
weight_size :: Int
w1_start = 0
w1_size = inputSize * hiddenSize
w2_start = w1_size + hiddenSize
w2_size = hiddenSize * outputSize
b2_start = w2_start + w2_size
weight\_size = w1\_size + hiddenSize + w2\_size + outputSize
```

# 3 Layers

#### 3.1 Affine

#### 3.1.1 forward

```
affine :: Mat \rightarrow Vec \rightarrow Mat \rightarrow Mat affine w b x = x \Leftrightarrow w + asRow b affineDX :: Mat \rightarrow Mat \rightarrow Mat affineDX w dout = dout \Leftrightarrow (tr w) affineDW :: Mat \rightarrow Mat \rightarrow [R] affineDW x dout = (matToList $ (tr x) \Leftrightarrow dout) ++ (toList $ sum $ toRows dout)
```

## 3.2 Activation Function

#### 3.2.1 ReLU

$$ReLU(x) = \max(x, 0)$$

$$ReLU(X) = \begin{bmatrix} ReLU(x_{11}) & \cdots & ReLU(x_{1N}) \\ \vdots & \ddots & \vdots \\ ReLU(x_{N1}) & \cdots & ReLU(x_{NN}) \end{bmatrix}$$

## 3.2.2 Sigmoid

$$\operatorname{sigmoid}(x) = \frac{1}{1 + e^{-x}}$$

```
\begin{array}{l} \text{sigmoid} :: R \rightarrow R \\ \text{sigmoid} \ x = 1 \ / \ (1 + \exp(-x)) \end{array}
```

# 3.3 Cross Entropy Error

$$ext{CEE}(m{y}, m{t}) = -m{t}^T egin{bmatrix} \ln y_1 \\ dots \\ \ln y_D \end{bmatrix}$$
 $ext{CEE}(Y, T) = \sum_{i=1}^N ext{CEE}(m{y}_i, m{t}_i)$ 

```
\begin{array}{c} \text{sumCrossEntropyError} :: [\text{Vec}] \to [\text{Vec}] \to \mathbb{R} \\ \text{sumCrossEntropyError} \ [] \ \_ = 0 \\ \text{sumCrossEntropyError} \ \_ \ [] = 0 \\ \text{sumCrossEntropyError} \ (y : y s) \ (t : t s) = -t <.> \ (\text{cmap log } y) + \\ \text{sumCrossEntropyError} \ ys \ ts \\ \text{crossEntropyError} \ :: \ \text{Mat} \to \text{Mat} \to \mathbb{R} \\ \text{crossEntropyError} \ y \ t = \text{sumCrossEntropyError} \ ys \ ts \ / \ \text{batchSize} \\ \text{where} \\ ys = toRows \ y \\ ts = toRows \ t \\ \text{batchSize} = \text{fromIntegral} \ \$ \ \text{length} \ ys \\ \end{array}
```

#### 3.4 Softmax

#### 3.4.1 Softmax

$$\exp(\boldsymbol{x}) = \begin{bmatrix} e^{x_1} \\ \vdots \\ e^{x_N} \end{bmatrix}$$

$$\operatorname{softmax}(\boldsymbol{x}) = \frac{\exp(\boldsymbol{x})}{\|\exp(\boldsymbol{x})\|_1} = \frac{\exp(\boldsymbol{x} - \boldsymbol{c})}{\|\exp(\boldsymbol{x} - \boldsymbol{c})\|_1}$$

$$\operatorname{softmax}(X) = \left[\operatorname{softmax}(\boldsymbol{x}_{:1}) \cdots \operatorname{softmax}(\boldsymbol{x}_{:N})\right]$$

#### 3.4.2 Softmax with Loss

#### 3.5 Loss Function

$$\mathcal{L}(\boldsymbol{w}; X, T) = \operatorname{softmaxWithLoss}(\hat{Y}, T)$$
$$= \operatorname{CEE}(\operatorname{softmax}(\hat{Y}), T)$$

```
\begin{array}{c} {\sf loss} \, :: \, {\sf Vec} \, \to \, {\sf Mat} \, \to \, {\sf Mat} \, \to \, {\sf R} \\ {\sf loss} \, \, {\sf w} \, \, {\sf x} \, \, {\sf t} = {\sf softmaxWithLoss} \, \, ({\sf forwardProp} \, \, {\sf w} \, \, {\sf x}) \, \, {\sf t} \end{array}
```

#### 3.6 One-Hot Vector

```
oneHotList :: Int \rightarrow Int \rightarrow [R] oneHotList len idx =
    if len == 0
        then []
    else
        if idx == 0
             then 1 : oneHotList (len - 1) (idx - 1)
        else 0 : oneHotList (len - 1) (idx - 1)

oneHotVector :: Int \rightarrow Int \rightarrow Vec
oneHotVector len idx = vector $ oneHotList len idx

oneHotMat :: Int \rightarrow [Int] \rightarrow Mat
oneHotMat len labelList = fromRows $ map (oneHotVector len)
labelList
```

## 3.7 Forward Propagetion

```
/
-- 出力層の活性化関数(softmax)を適用する直前まで計算
forwardProp :: Vec → Mat → Mat
forwardProp weight x = affine w2 b2 $ relu $ affine w1 b1 x
```

#### 3.8 Prediction

```
\begin{array}{lll} & & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & \\ & & \\ & \\ & & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\
```

#### 3.9 Gradient

```
\texttt{numericalGradientList} \ :: \ \texttt{Int} \ \rightarrow \ \texttt{(Vec} \ \rightarrow \ \texttt{R)} \ \rightarrow \ \texttt{Vec} \ \rightarrow \ \texttt{[R]}
numericalGradientList idx f x =
     if idx == size x
           then []
           else
                 let h = 1e-4
                      dx = cmap (* h) $ oneHotVector (size x) idx
                      x1 = x + dx
                      x2 = x - dx
                 in (f(x1) - f(x2)) / (2 * h): numericalGradientList (
                      idx + 1) f x
{\tt numericalGradient} \; :: \; ({\tt Vec} \; \rightarrow \; {\tt R}) \; \rightarrow \; {\tt Vec} \; \rightarrow \; {\tt Vec}
numericalGradient f = vector \circ (numericalGradientList 0 f)
\mathtt{matToList} :: \mathtt{Mat} \rightarrow [\mathtt{R}]
{\tt matToList} = {\tt concat} \circ {\tt toLists}
{	t gradient} :: {	t Vec} 
ightarrow {	t Mat} 
ightarrow {	t Mat} 
ightarrow {	t Vec}
gradient weight x t =
     let w1 = reshape hiddenSize $ subVector w1_start w1_size weight
           :: Mat
           w2 = reshape outputSize $ subVector w2_start w2_size weight
                :: Mat
           b1 = subVector w1_size hiddenSize weight
           b2 = subVector b2_start outputSize weight
           -- forward propagation
           a1 = affine w1 b1 x
           y1 = relu a1
```

```
y2 = softmax $ affine w2 b2 y1
         -- backward propagation
         da2 = softmaxWithLossBackward y2 t
         dx2 = affineDX w2 da2
         dw2 = affineDW y1 da2
         da1 = reluBackward dx2 a1
         dw1 = affineDW x da1
    in fromList dw1 + dw2
\texttt{gradientCheck} \; :: \; \texttt{Vec} \; \rightarrow \; \texttt{Mat} \; \rightarrow \; \texttt{R}
gradientCheck w x t =
    let num_grad
                      = numericalGradient (\lambda_w 
ightarrow loss _w x t) w
         grad
                       = gradient w x t
                       = sum $ map abs $ toList $ num_grad - grad
    in err_sum / (fromIntegral $ length $ toList grad)
```

## 3.10 Learning

```
learn :: Vec \rightarrow Mat \rightarrow Mat \rightarrow R \rightarrow R \rightarrow Vec learn weight x t learningRate iterNum = if iterNum == 0 then weight else learn new_w x t learningRate (iterNum - 1) where new_w = weight - (cmap (* learningRate) $ gradient weight x t) testAccuracy :: Vec \rightarrow Mat \rightarrow Mat \rightarrow R testAccuracy w x t = scoreSum / (fromIntegral $ rows x) where scoreSum = sumElements $ takeDiag $ (predict w x) \Leftrightarrow (tr t )
```