Assignment 04

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Binary classification based on 3 layers neural network

First layer

$Z^{[1]} = W^{[1]}X + b^{[1]}$: X denotes the input data $A^{[1]} = g^{[1]}(Z^{[1]})$: $g^{[1]}$ is the activation function at the first layer

Second layer

$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$

$A^{[2]} = g^{[2]}(Z^{[2]})$: $g^{[2]}$ is the activation function at the second layer

Third layer

$Z^{[3]} = W^{[3]}A^{[2]} + b^{[3]}$

$A^{[3]} = g^{[3]}(Z^{[3]})$: $g^{[3]}$ is the activation function at the third (output) layer

import library & plot functions

In [1]:

```
import matplotlib.pyplot as plt
import numpy as np
import time

import torch
from torch.utils.data import Dataset, DataLoader
import torchvision.transforms as transforms
import torchvision
```

In [2]:

```
def output_plot(g1, g2, title, color, label, legend):
    plt.title(title)
    plt.plot(np.arange(1, len(g1) + 1), g1, color=color[0], alpha=0.5, label=label[0])
    plt.plot(np.arange(1, len(g2) + 1), g2, color=color[1], alpha=0.5, label=label[1])
    plt.legend(loc=legend)
    plt.show()


def output_frame_plot(tloss, vloss, tacc, vacc, title):
    print(" << %s >>" % title)
    print("----------------------------------------")
    print("           |   loss    |  accuracy  |")
    print("----------------------------------------")
```

```
    print("training   |   %.2f   |    %.2f    |" % (tloss, tacc))
    print("----------------------------------------")
    print("validation |   %.2f   |    %.2f    |" % (vloss, vacc))
    print("----------------------------------------")
```

Declare the constants

In [3]:

```
IMAGE_WIDTH = 100
IMAGE_HEIGHT = 100
IMAGE_CHANNEL = 1
DIMENSION = IMAGE_CHANNEL * IMAGE_HEIGHT * IMAGE_WIDTH
```

Load train & validation datasets (preprocess)

- batch size = 3
- number of workers = 1 (main process + worker1)
- number of epoch = 1

In [4]:

```
def pre_process(batch_size=3, num_workers=1):
    transform = transforms.Compose([  # transforms.Resize((256,256)),
        transforms.Grayscale(),
        # the code transforms.Graysclae() is for changing the size [3,100,100] to [1, 100,␣
↪100] (notice : [channel, height, width] )
        transforms.ToTensor(), ])

    # train_data_path = 'relative path of training data set'
    train_data_path = './horse-or-human/train'
    trainset = torchvision.datasets.ImageFolder(root=train_data_path, transform=transform)
    # change the valuse of batch_size, num_workers for your program
    # if shuffle=True, the data reshuffled at every epoch
    trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,␣
↪shuffle=False, num_workers=num_workers)

    validation_data_path = './horse-or-human/validation'
    valset = torchvision.datasets.ImageFolder(root=validation_data_path,␣
↪transform=transform)
    # change the valuse of batch_size, num_workers for your program
    valloader = torch.utils.data.DataLoader(valset, batch_size=batch_size, shuffle=False,␣
↪num_workers=num_workers)

    train_data = np.empty((DIMENSION, 0))
    validation_data = np.empty((DIMENSION, 0))

    train_label = np.array([])
    validation_label = np.array([])

    for i, data in enumerate(trainloader):
```

```python
        # inputs is the image
        # labels is the class of the image
        inputs, labels = data

        # if you don't change the image size, it will be [batch_size, 1, 100, 100]

        # [batch_size, 1, height, width] => [ width * height * channel, batch_size ]
        x = np.array(inputs).transpose((2, 3, 0, 1)).reshape((DIMENSION, len(labels)))
        train_data = np.concatenate((train_data, x), axis=1)
        train_label = np.concatenate((train_label, np.array(labels)))

    # load validation images of the batch size for every iteration
    for i, data in enumerate(valloader):
        # inputs is the image
        # labels is the class of the image
        inputs, labels = data

        # [batch_size, 1, height, width] => [ width * height * channel, batch_size ]
        x = np.array(inputs).transpose((2, 3, 0, 1)).reshape((DIMENSION, len(labels)))
        validation_data = np.concatenate((validation_data, x), axis=1)
        validation_label = np.concatenate((validation_label, np.array(labels)))

    return train_data, validation_data, train_label, validation_label


t_data, v_data, t_label, v_label = pre_process(batch_size=3, num_workers=1)
```

Implements of 3 layers neural network

Activation Functions

1. sigmoid

$g(z) = \frac{1}{1+\exp^{-z}}$

2. tanh

$g(z) = \frac{\exp^{z} - \exp^{-z}}{\exp^{z} + \exp^{-z}}$

3. ReLU

$g(z) = \max(0, z)$

4. Leaky ReLU

$g(z) = \max(0.01z, z)$

Architecture

- epsilon : $\rceil = 10^{-6}$
- initialization : $Var(w_i) = \frac{2}{n_{in}+n_{out}}$

Input layer

- num of features = 10000 (100 * 100 image)

- num of samples = 1027 (number of training image samples)

hidden layer 1

- num of features (nodes) = 150

hidden layer 2

- num of features (nodes) = 50

output layer

- num of features (nodes) = 1

In [5]:

```
# binary classifier
def binary_classify(train_data, validation_data,
                    train_label, validation_label,
                    gn_act, gn_d_act, learning_rate=0.0002):

    num_of_layers = 3
    n1, n2 = 150, 50
    learning_rate = learning_rate
    epsilon = 10e-6

    # INITIALIZE u v z
    u = np.random.randn(DIMENSION, n1) * np.sqrt(2 / (DIMENSION + n1))
    v = np.random.randn(n1, n2) * np.sqrt(2 / (n1 + n2))
    w = np.random.randn(n2, 1) * np.sqrt(2 / (n2 + 1))

    # INITIALIZE bias
    b1 = np.random.randn(n1, 1)
    b2 = np.random.randn(n2, 1)
    b3 = np.random.randn(1, 1)

    train_losses = []
    test_losses = []
    train_accuracies = []
    test_accuracies = []

    def cross_entropy(prob, ans):
        return -(ans * np.log(np.nan_to_num(prob)) + (1 - ans) * np.log(np.
↪nan_to_num(1-prob)))
        # return -(ans * safe_ln(prob) + (1 - ans) * safe_ln(1-prob))

    def loss(prob, ans):
        return (1 / len(ans)) * np.nan_to_num(np.sum(cross_entropy(prob, ans)))

    def accuracy(prob, ans):
        arr = np.array(list(map(lambda x: 1 if x > 0.5 else 0, prob.flatten())))
        arr = list(filter(lambda x: x == 0, arr - ans))
        return len(arr) / len(ans)

    def iterate():
```

```
        p_train_loss = 0
        nonlocal u, v, w, b1, b2, b3
        nonlocal train_losses, test_losses, train_accuracies, test_accuracies

        while True:

            # forward propagation #
            act = gn_act()
            next(act)
            z1 = np.dot(u.T, train_data) + b1
            a1 = act.send(z1)

            z2 = np.dot(v.T, a1) + b2
            a2 = act.send(z2)

            z3 = np.dot(w.T, a2) + b3
            a3 = act.send(z3)

            act = gn_act()
            next(act)
            vz = np.dot(u.T, validation_data) + b1
            vz = np.dot(v.T, act.send(vz)) + b2
            vz = np.dot(w.T, act.send(vz)) + b3
            ####

            # back propagation #
            d_act = gn_d_act()
            next(d_act)

            cw = (a3 - train_label)
            dw = np.dot(cw, a2.T) / z3.shape[1]

            cv = np.dot(w, cw) * d_act.send(z2)
            dv = np.dot(cv, a1.T) / z3.shape[1]

            cu = np.dot(v, cv) * d_act.send(z1)
            du = np.dot(cu, train_data.T) / z3.shape[1]

            b3 = b3 - (learning_rate * (np.sum(cw, axis=1, keepdims=True) / z3.shape[1]))
            b2 = b2 - (learning_rate * (np.sum(cv, axis=1, keepdims=True) / z3.shape[1]))
            b1 = b1 - (learning_rate * (np.sum(cu, axis=1, keepdims=True) / z3.shape[1]))

            # gradient descent #
            w = w - (learning_rate * dw).T
            v = v - (learning_rate * dv).T
            u = u - (learning_rate * du).T
            ####

            # get losses
            t_hat, v_hat = a3, act.send(vz)
```

```
            n_train_loss = loss(t_hat, train_label)
            n_test_loss = loss(v_hat, validation_label)

            # get accuracies
            n_train_acc = accuracy(t_hat, train_label)
            n_test_acc = accuracy(v_hat, validation_label)

            train_losses.append(n_train_loss)
            test_losses.append(n_test_loss)
            train_accuracies.append(n_train_acc)
            test_accuracies.append(n_test_acc)

            if abs(p_train_loss - n_train_loss) < epsilon:
                break
            else:
                # print('t loss: %s, v loss: %s' % (n_train_loss, n_test_loss))
                p_train_loss = n_train_loss
                continue

    iterate()

    return train_losses, test_losses, train_accuracies, test_accuracies
```

Case Studies

implementations

In [6]:

```
def learn(case, title):

    leaky_alpha = 0.01

    t_data, v_data, t_label, v_label = pre_process(batch_size=3, num_workers=1)
    train_loss, test_loss, train_acc, test_acc = [], [], [], []

    # functions
    def sigmoid(z):
        return 1 / (1 + np.exp(-z))

    def d_sigmoid(z):
        return sigmoid(z) * (1 - sigmoid(z))

    def tanh(z):
        return (np.exp(z) - np.exp(-z)) / (np.exp(z) + np.exp(-z))

    def d_tanh(z):
        return 1 - (tanh(z) ** 2)

    def relu(z):
```

```python
        return np.maximum(0, z)

    def d_relu(z):
        return np.where(z <= 0, 0, 1)

    def leaky_relu(z):
        return np.maximum(leaky_alpha * z, z)

    def d_leaky_relu(z):
        return np.where(z <= 0, leaky_alpha, 1)

    # case-studies
    def case1(learning_rate):
        def act():
            z = yield
            z = yield sigmoid(z)
            z = yield sigmoid(z)
            z = yield sigmoid(z)

        def d_act():
            z = yield
            z = yield d_sigmoid(z)
            z = yield d_sigmoid(z)

        classify(gn=act, dgn=d_act, learning_rate=learning_rate)
        plot()

    def case2(learning_rate):
        def act():
            z = yield
            z = yield tanh(z)
            z = yield tanh(z)
            z = yield sigmoid(z)

        def d_act():
            z = yield
            z = yield d_tanh(z)
            z = yield d_tanh(z)

        classify(gn=act, dgn=d_act, learning_rate=learning_rate)
        plot()

    def case3(learning_rate):
        def act():
            z = yield
            z = yield relu(z)
            z = yield relu(z)
            z = yield sigmoid(z)

        def d_act():
            z = yield
```

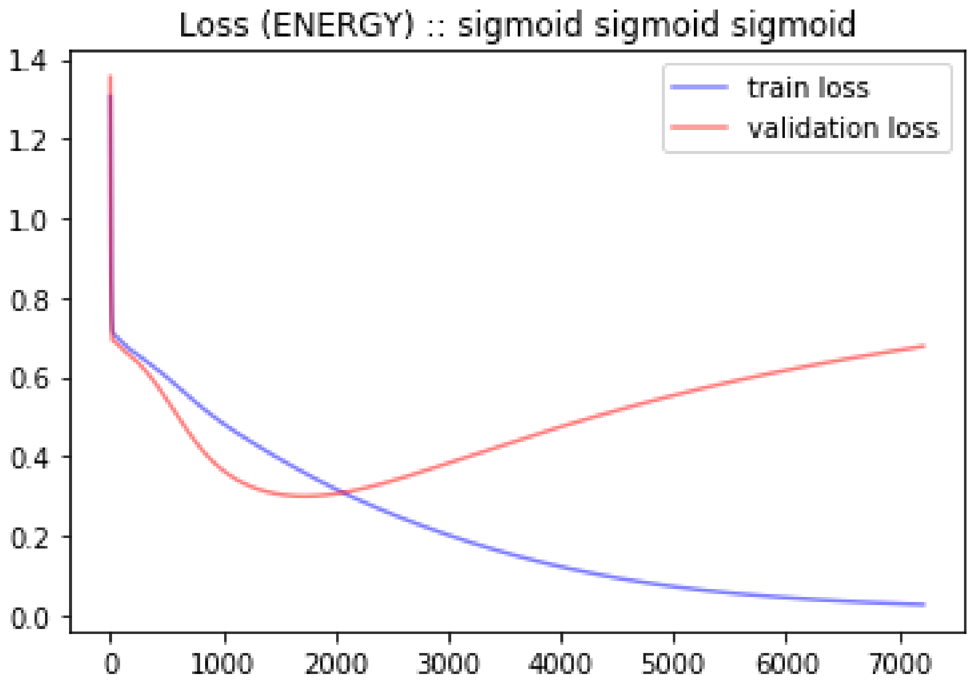
```python
            z = yield d_relu(z)
            z = yield d_relu(z)

        classify(gn=act, dgn=d_act, learning_rate=learning_rate)
        plot()

    def case4(learning_rate):
        def act():
            z = yield
            z = yield leaky_relu(z)
            z = yield leaky_relu(z)
            z = yield sigmoid(z)

        def d_act():
            z = yield
            z = yield d_leaky_relu(z)
            z = yield d_leaky_relu(z)

        classify(gn=act, dgn=d_act, learning_rate=learning_rate)
        plot()

    def classify(gn, dgn, learning_rate):
        nonlocal train_loss, test_loss, train_acc, test_acc

        train_loss, test_loss, train_acc, test_acc = binary_classify(
            t_data, v_data,
            t_label, v_label,
            gn, dgn, learning_rate
        )

    def plot():
        output_plot(train_loss, test_loss,
                    title="Loss (ENERGY) :: " + title, color=('blue', 'red'),
                    label=('train loss', 'validation loss'), legend='upper right')

        output_plot(train_acc, test_acc,
                    title="Accuracy :: " + title, color=('blue', 'red'),
                    label=('train accuracy', 'validation accuracy'), legend='lower right')

        output_frame_plot(train_loss[-1], test_loss[-1], train_acc[-1], test_acc[-1],
↪title=title)

    if case == 1:
        case1(learning_rate=0.015)
    elif case == 2:
        case2(learning_rate=0.0005)
    elif case == 3:
        case3(learning_rate=0.0005)
    elif case == 4:
        case4(learning_rate=0.0005)
```

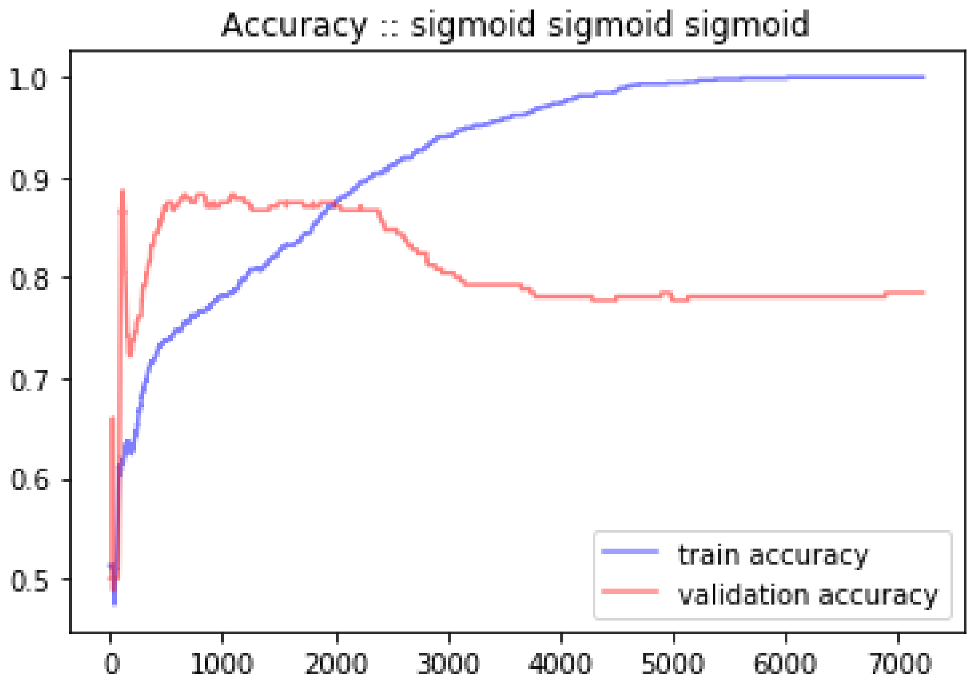
case 1

- $g^{[1]}, g^{[2]}, g^{[3]}$ are Sigmoid
- learning rate : 0.015
- initialization : $Var(w_i) = \frac{2}{n_{in}+n_{out}}$

In [7]:

```
learn(case=1, title="sigmoid sigmoid sigmoid")
```





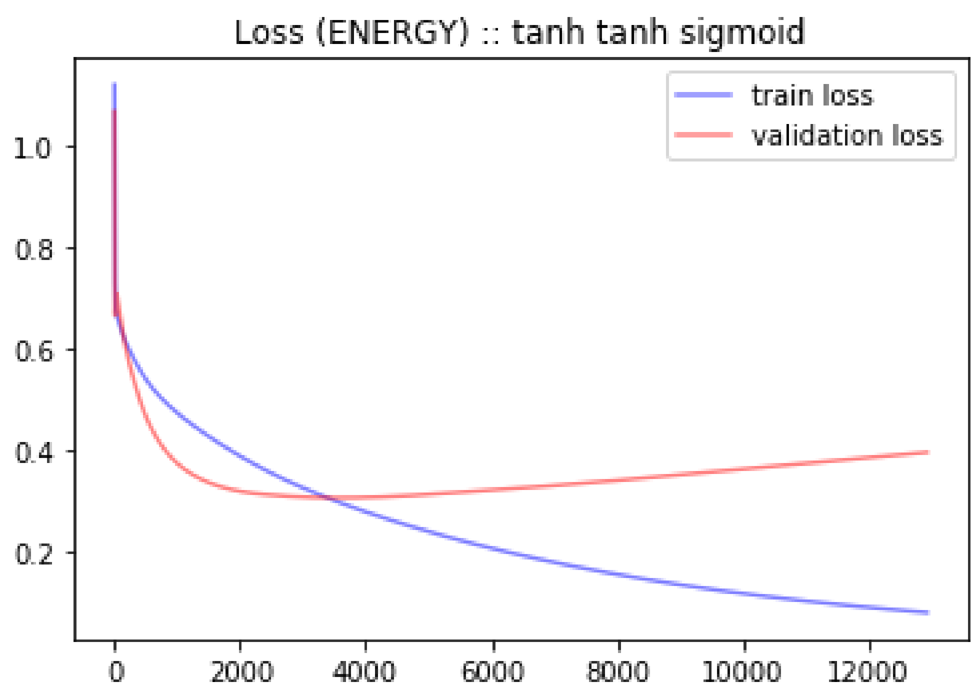
```
 << sigmoid sigmoid sigmoid >>
---------------------------------------
           |   loss    |  accuracy  |
---------------------------------------
training   |   0.03    |    1.00    |
---------------------------------------
validation |   0.68    |    0.79    |
---------------------------------------
```

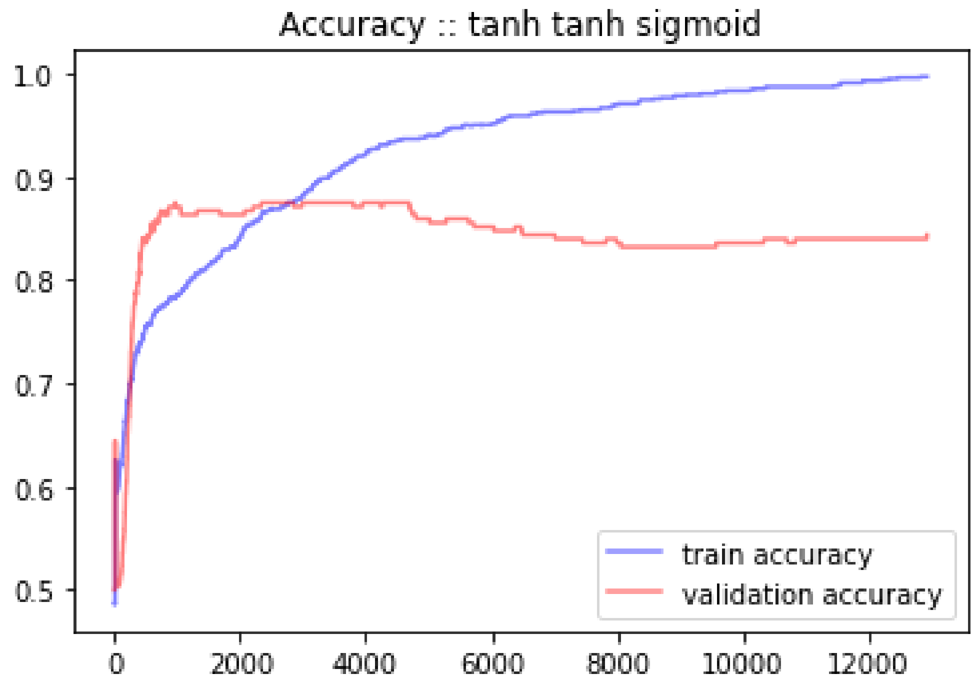
case 2

- $g^{[1]}, g^{[2]}$ are tanh and $g^{[3]}$ is Sigmoid
- learning rate = 0.0005
- initialization : $Var(w_i) = \frac{2}{n_{in}+n_{out}}$

In [8]:

```
learn(case=2, title="tanh tanh sigmoid")
```





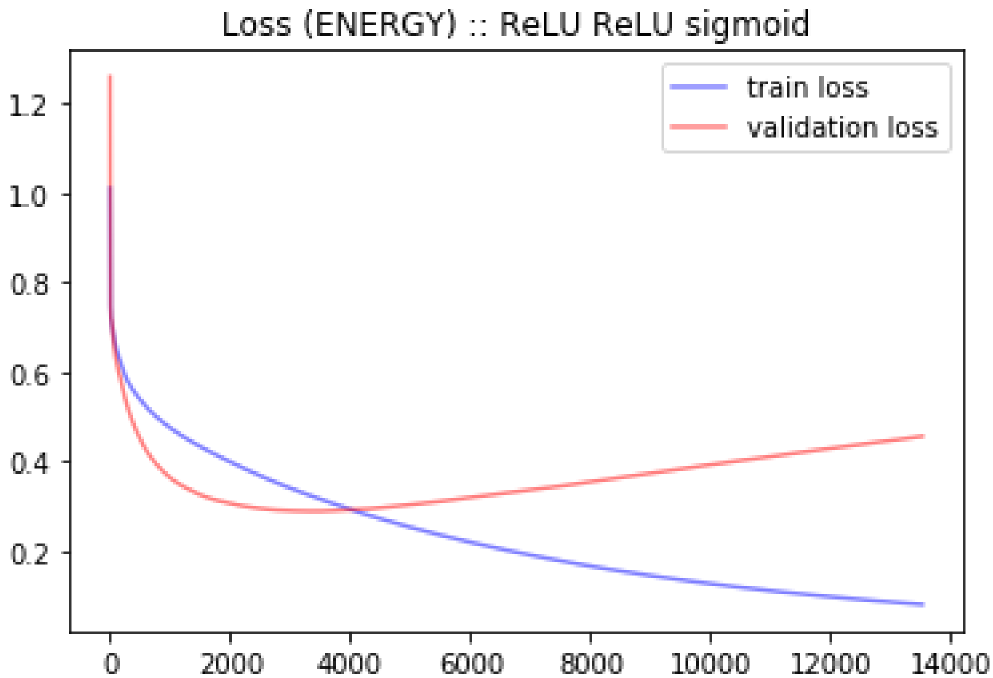

```
 << tanh tanh sigmoid >>
---------------------------------------
           |   loss    |  accuracy  |
---------------------------------------
training   |   0.08    |    1.00    |
---------------------------------------
validation |   0.39    |    0.84    |
---------------------------------------
```

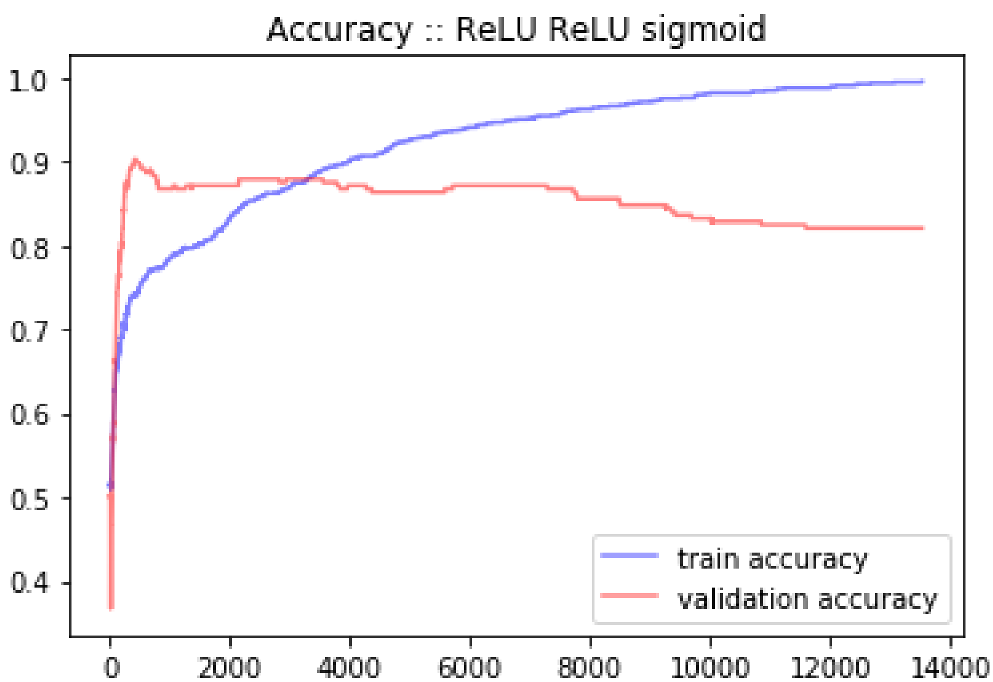
case 3

- $g^{[1]}, g^{[2]}$ are ReLU and $g^{[3]}$ is Sigmoid
- learning rate = 0.0005
- initialization : $Var(w_i) = \frac{2}{n_{in}+n_{out}}$

In [9]:

```
learn(case=3, title="ReLU ReLU sigmoid")
```





<< ReLU ReLU sigmoid >>

	loss	accuracy
training	0.08	1.00
validation	0.46	0.82

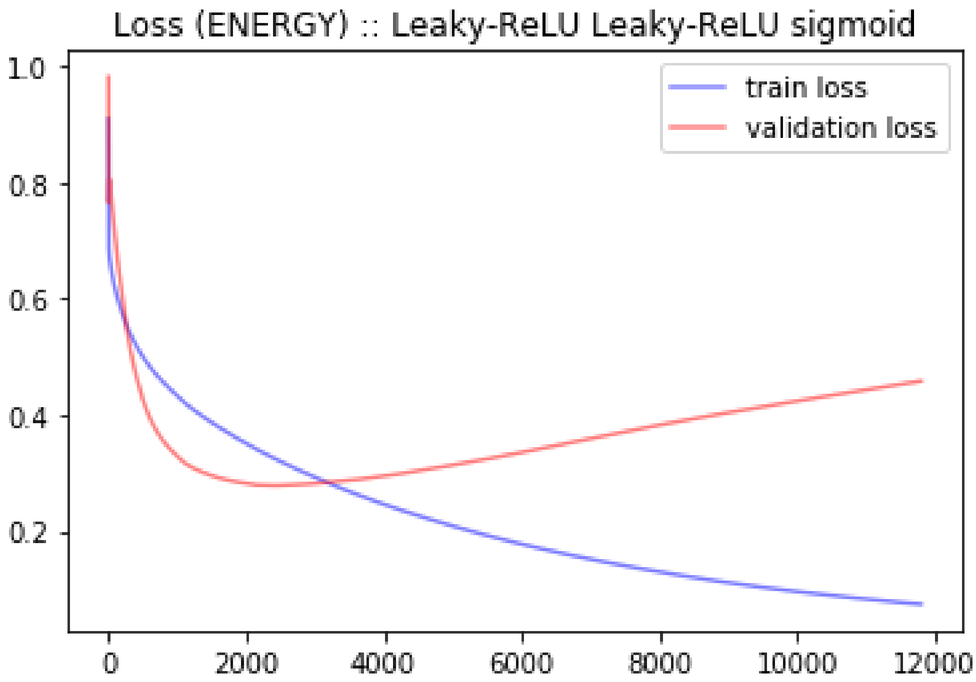
----

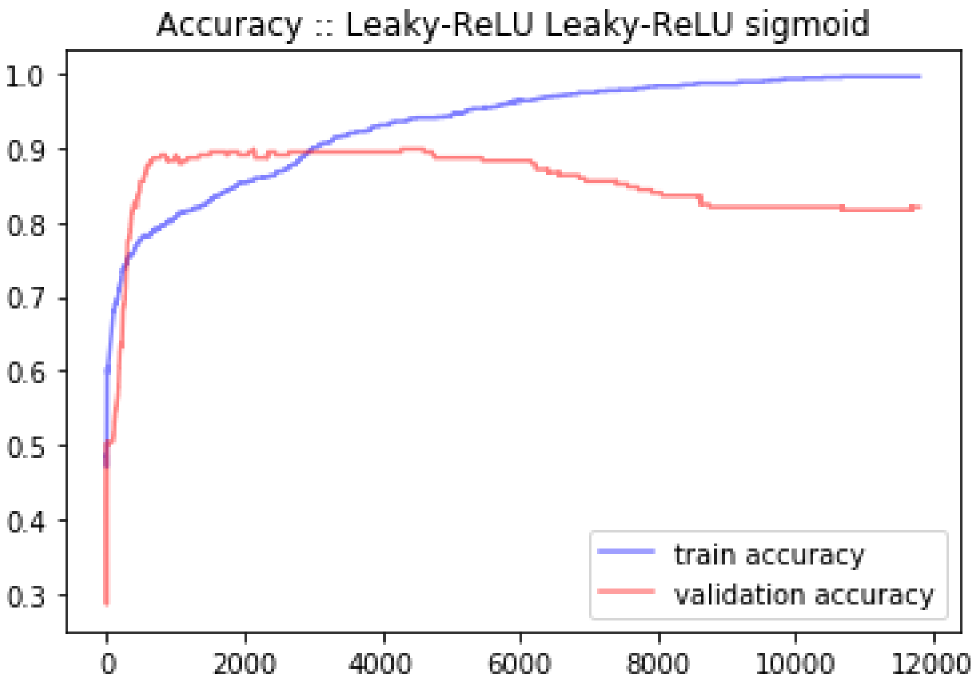
case 4

- $g^{[1]}, g^{[2]}$ are Leaky ReLU ($\alpha = 0.01$) and $g^{[3]}$ is Sigmoid
- learning rate $= 0.0005$
- initialization : $Var(w_i) = \frac{2}{n_{in}+n_{out}}$

In [10]:

```
learn(case=4, title="Leaky-ReLU Leaky-ReLU sigmoid")
```






```
 << Leaky-ReLU Leaky-ReLU sigmoid >>
---------------------------------------
           |   loss    |  accuracy  |
---------------------------------------
training   |   0.08    |    1.00    |
---------------------------------------
validation |   0.46    |    0.82    |
---------------------------------------
```