ExerciseRound09

November 7, 2024

[1]:
```
# This cell is used for creating a button that hides/unhides code cells to␣
↪quickly look only the results.
# Works only with Jupyter Notebooks.

from IPython.display import HTML

HTML('''<script>
code_show=true;
function code_toggle() {
if (code_show){
$('div.input').hide();
} else {
$('div.input').show();
}
code_show = !code_show
}
$( document ).ready(code_toggle);
</script>
<form action="javascript:code_toggle()"><input type="submit" value="Click here␣
↪to toggle on/off the raw code."></form>''')
```

[1]: <IPython.core.display.HTML object>

[2]:
```
# Description:
#   Exercise09 notebook.
#
# Copyright (C) 2018 Santiago Cortes, Juha Ylioinas
#
# This software is distributed under the GNU General Public
# Licence (version 2 or later); please refer to the file
# Licence.txt, included with the software, for details.

# Preparations
import os
import numpy as np
import matplotlib.pyplot as plt
```

```python
from utils import from_data_file, theta_to_model, model_to_theta,␣
 ↪initial_model, logistic, \
    log_sum_exp_over_rows, classification_performance

# Select data directory

if os.path.isdir('/coursedata'):
    # JupyterHub
    course_data_dir = '/coursedata'
elif os.path.isdir('../../../coursedata'):
    # Local installation
    course_data_dir = '../../../coursedata'
else:
    # Docker
    course_data_dir = '/home/jovyan/work/coursedata/'

print('The data directory is %s' % course_data_dir)
data_dir = os.path.join(course_data_dir, 'exercise-09-data')
print('Data stored in %s' % data_dir)
```

```
The data directory is /coursedata
Data stored in /coursedata/exercise-09-data
```

1 CS-E4850 Computer Vision Exercise Round 9

The problems should be solved before the exercise session and solutions returned via MyCourses. Upload the files: (1) a pdf file containing your written answers to Exercise 1, and (2) both the pdf and .ipynb versions of the notebook containing your answers to Exercises 2 and 3. Scanned, **neatly** handwritten, solutions are ok for problem 1. If possible, combine your pdf solution of Exercise 1 with the notebook pdf into a single pdf and return that with the notebook .ipynb file.

Notice also that the last two problems can be done without solving Exercise 1 since the solutions are already written out in the subtasks of Exercise 1 (i.e. only the derivations are missing and asked in Exercise 1).

If you have not studied basics of neural networks in previous courses and the problem context of these exercises is not clear, it may be helpful to check the slides of the first four lectures of prof. Hinton's course "Introduction to neural networks and machine learning":
http://www.cs.toronto.edu/~hinton/coursera_slides.html
http://www.cs.toronto.edu/~hinton/coursera_lectures.html (lecture videos).

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1.1 Exercise 1 - Neural networks and backpropagation

This is a pen-&-paper problem. See Exercise09penandpaper.pdf for the questions.

1.2 Exercise 2 - Image classification using a neural network

The first exercise problem above gives the solution to Part 2 of the second programming assignment of professor Hinton's course "Introduction to neural networks and machine learning". The assignment and related material are available at https://www.cs.toronto.edu/~tijmen/csc321/assignments/a2/.

Check out the contents of the above web page and complete the programming task of Part 2 according to the instructions given there. The code template for the python version is below. The solution for the pen and paper part of the task is already given above in **Exercise 1**. Hence, the programming part is a relatively straightforward implementation and can be done without carrying out the derivations since the results of the derivations are already given in **Exercise 1** above.

[3]:
```
def test_gradient(model, data, wd_coefficient):
    import sys
    base_theta = model_to_theta(model)
    h = 1e-2
    correctness_threshold = 1e-5
    analytic_gradient_struct = d_loss_by_d_model(model, data, wd_coefficient)

    analytic_gradient = model_to_theta(analytic_gradient_struct);
    if True in np.isnan(analytic_gradient) or True in np.
↪isinf(analytic_gradient):
        sys.exit('Your gradient computation produced a NaN or infinity. That is␣
↪an error.')
    # We want to test the gradient not for every element of theta, because␣
↪that's a
    # lot of work. Instead, we test for only a few elements. If there's an␣
↪error, this
    # is probably enough to find that error.
    # We want to first test the hid_to_class gradient, because that's most␣
↪likely
    # to be correct (it's the easier one).
    # Let's build a list of theta indices to check. We'll check 20 elements of
    # hid_to_class, and 80 elements of input_to_hid (it's bigger than␣
↪hid_to_class).
    input_to_hid_theta_size = model['input_to_hid'].size
    hid_to_class_theta_size = model['hid_to_class'].size
    big_prime = 1299721; # 1299721 is prime and thus ensures a somewhat␣
↪random-like selection of indices.
    hid_to_class_indices_to_check = np.mod(big_prime * np.arange(20),␣
↪hid_to_class_theta_size) \
                                    + input_to_hid_theta_size
    input_to_hid_indices_to_check = np.mod(big_prime * np.arange(80),␣
↪input_to_hid_theta_size)
    a = hid_to_class_indices_to_check[np.newaxis,:]
    b = input_to_hid_indices_to_check[np.newaxis,:]
    indices_to_check = np.ravel(np.hstack((a,b)))
```

```
    for i in range(100):
        test_index = indices_to_check[i]
        analytic_here = analytic_gradient[test_index]
        theta_step = base_theta * 0
        theta_step[test_index] = h
        contribution_distances = np.array([-4.,  -3.,  -2.,  -1.,   1.,   2.,   3.,   4.])
        contribution_weights = np.array([1/280., -4/105., 1/5., -4/5., 4/5., -1/5., 4/105., -1/280.])
        temp = 0;
        for contribution_index in range(8):
            temp = temp + loss(theta_to_model(base_theta + theta_step * \
                                                             contribution_distances[contribution_index]), data, wd_coefficient) * \
                                                               contribution_weights[contribution_index]
        fd_here = temp / h
        diff = np.abs(analytic_here - fd_here)

        if True in (diff > correctness_threshold) and \
            True in (diff / (np.abs(analytic_here) + np.abs(fd_here)) > correctness_threshold):
            part_names = ['input_to_hid', 'hid_to_class']
            sys.exit('Theta element #{} (part of {}), with value {}, has finite difference gradient {} but analytic gradient {}. That looks like an error.\n'.format(test_index, part_names[(i<20)], base_theta[test_index], fd_here, analytic_here))
        if i==19:
            print('Gradient test passed for hid_to_class. ')
        if i==99:
            print('Gradient test passed for input_to_hid. ')
    print('Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).\n')

def forward_pass(model, data):
    # This function does the forward pass through the network: calculating the states of all units, and some related data.
    # This function is used in functions loss() and d_loss_by_d_model().

    # model.input_to_hid is a matrix of size <number of hidden units> by <number of inputs i.e. 256>. It contains the weights from the input units to the hidden units.
```

```python
    # model.hid_to_class is a matrix of size <number of classes i.e. 10> by <number of hidden units>. It contains the weights from the hidden units to the softmax units.
    # data.inputs is a matrix of size <number of inputs i.e. 256> by <number of data cases>. Each column describes a different data case.
    # data.targets is a matrix of size <number of classes i.e. 10> by <number of data cases>. Each column describes a different data case. It contains a one-of-N encoding of the class, i.e. one element in every column is 1 and the others are 0.

    hid_input = np.dot(model['input_to_hid'], data['inputs']) # input to the hidden units, i.e. before the logistic. size: <number of hidden units> by <number of data cases>
    hid_output = logistic(hid_input) # output of the hidden units, i.e. after the logistic. size: <number of hidden units> by <number of data cases>
    class_input = np.dot(model['hid_to_class'], hid_output) # input to the components of the softmax. size: <number of classes, i.e. 10> by <number of data cases>

    # The following three lines of code implement the softmax.
    # However, it's written differently from what the lectures say.
    # In the lectures, a softmax is described using an exponential divided by a sum of exponentials.
    # What we do here is exactly equivalent (you can check the math or just check it in practice), but this is more numerically stable.
    # "Numerically stable" means that this way, there will never be really big numbers involved.
    # The exponential in the lectures can lead to really big numbers, which are fine in mathematical equations, but can lead to all sorts of problems in Matlab
    # Matlab isn't well prepared to deal with really large numbers, like the number 10 to the power 1000. Computations with such numbers get unstable, so we avoid them.

    class_normalizer = log_sum_exp_over_rows(class_input) # log(sum(exp of class_input)) is what we subtract to get properly normalized log class probabilities. size: <1> by <number of data cases>
    log_class_prob = class_input - np.tile(class_normalizer, (class_input.shape[0], 1)) # log of probability of each class. size: <number of classes, i.e. 10> by <number of data cases>
    class_prob = np.exp(log_class_prob) # probability of each class. Each column (i.e. each case) sums to 1. size: <number of classes, i.e. 10> by <number of data cases>

    return hid_input, hid_output, class_input, log_class_prob, class_prob
```

```
def loss(model, data, wd_coefficient):
    hid_input, hid_output, class_input, log_class_prob, class_prob =␣
↪forward_pass(model, data);
    classification_loss = -np.mean(np.sum(np.multiply(log_class_prob,␣
↪data['target']), 0)) # select the right log class probability using that sum;
↪ then take the mean over all data cases.
    wd_loss = (np.sum(np.ravel(model['input_to_hid']) ** 2 ) + np.sum(np.
↪ravel(model['hid_to_class']) ** 2 )) / 2. * wd_coefficient; # weight decay␣
↪loss. very straightforward: E = 1/2 * wd_coeffecient * parameters^2
    ret = classification_loss + wd_loss
    return ret
```

[4]:
```
def d_loss_by_d_model(model, data, wd_coefficient):
    # model.input_to_hid is a matrix of size <number of hidden units> by␣
↪<number of inputs i.e. 256>
    # model.hid_to_class is a matrix of size <number of classes i.e. 10> by␣
↪<number of hidden units>
    # data.inputs is a matrix of size <number of inputs i.e. 256> by <number of␣
↪data cases>
    # data.targets is a matrix of size <number of classes i.e. 10> by <number␣
↪of data cases>

    # The returned object <ret> is supposed to be exactly like parameter␣
↪<model>, i.e. it has fields ret.input_to_hid and ret.hid_to_class, and those␣
↪are of the same shape as they are in <model>.
    # However, in <ret>, the contents of those matrices are gradients (d loss␣
↪by d weight), instead of weights.
    ret = dict()
    # This is the only function that you're expected to change. Right now, it␣
↪just returns a lot of zeros, which is obviously not the correct output. Your␣
↪job is to change that.
    #--your-code-starts-here--#

    # Forward pass
    hid_input, hid_output, class_input, log_class_prob, class_prob =␣
↪forward_pass(model, data)

    # Error signal output layer
    output_error = class_prob - data['target']

    # Gradient
    ret['hid_to_class'] = np.dot(output_error, hid_output.T) / data['inputs'].
↪shape[1]

    # Error signal hidden layer
    def logistic_derivative(hid_input):
```

```
        hid_output = logistic(hid_input)
        return hid_output * (1 - hid_output)
    hidden_error = np.dot(model['hid_to_class'].T, output_error) *␣
↪logistic_derivative(hid_input)

    # Gradient
    ret['input_to_hid'] = np.dot(hidden_error, data['inputs'].T) /␣
↪data['inputs'].shape[1]

    # Weight decay
    ret['hid_to_class'] += wd_coefficient * model['hid_to_class']
    ret['input_to_hid'] += wd_coefficient * model['input_to_hid']

    return ret
    #--your-code-ends-here--#
    return ret
```

[5]:
```
def a2(wd_coefficient, n_hid, n_iters, learning_rate, momentum_multiplier,␣
↪do_early_stopping, mini_batch_size):
    model = initial_model(n_hid)
    datas = from_data_file(data_dir)

    n_training_cases = datas['train']['inputs'].shape[1]
    if n_iters != 0:
        print("Now testing the gradient on the whole training set...")
        test_gradient(model, datas['train'], wd_coefficient)

    # optimization
    training_batch = dict()
    best_so_far = dict()
    theta = model_to_theta(model)
    momentum_speed = theta * 0.
    training_data_losses = []
    validation_data_losses = []
    if do_early_stopping:
        best_so_far['theta'] = -1 # this will be overwritten soon
        best_so_far['validation_loss'] = np.Inf
        best_so_far['after_n_iters'] = -1

    for optimization_iteration_i in range(1, n_iters+1):
        model = theta_to_model(theta)
        training_batch_start = np.mod((optimization_iteration_i-1) *␣
↪mini_batch_size, n_training_cases);
        training_batch['inputs'] = datas['train']['inputs'][:,␣
↪training_batch_start : training_batch_start + mini_batch_size]
        training_batch['target'] = datas['train']['target'][:,␣
↪training_batch_start : training_batch_start + mini_batch_size]
```

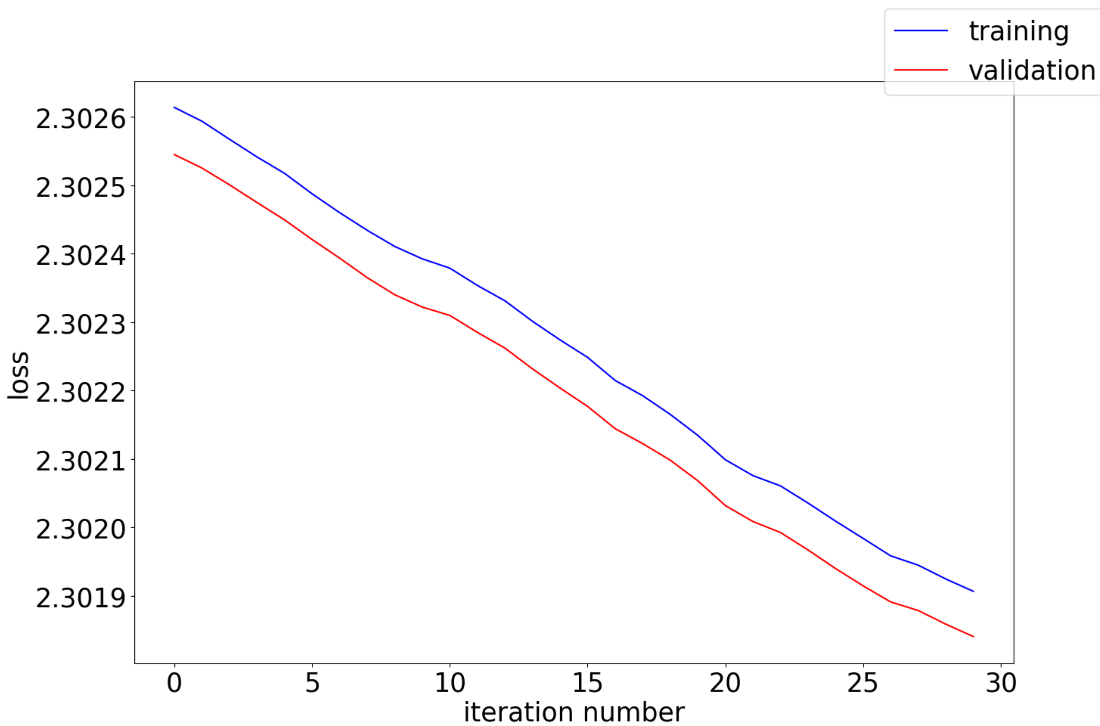
```
        gradient = model_to_theta(d_loss_by_d_model(model, training_batch, wd_coefficient))
        momentum_speed = np.multiply(momentum_speed, momentum_multiplier) - gradient;
        theta = theta + momentum_speed * learning_rate;
        model = theta_to_model(theta);
        training_data_losses.append(loss(model, datas['train'], wd_coefficient))
        validation_data_losses.append(loss(model, datas['val'], wd_coefficient))

        if do_early_stopping and validation_data_losses[-1] < best_so_far['validation_loss']:
            best_so_far['theta'] = theta; # this will be overwritten soon
            best_so_far['validation_loss'] = validation_data_losses[-1]
            best_so_far['after_n_iters'] = optimization_iteration_i

        if np.mod(optimization_iteration_i, np.round(n_iters / 10.)) == 0:
            print('After {} optimization iterations, training data loss is {}, and validation data loss is {}\n'.format(optimization_iteration_i, training_data_losses[-1], validation_data_losses[-1]))

        if optimization_iteration_i == n_iters: # check gradient again, this time with more typical parameters and with a different data size
            print('Now testing the gradient on just a mini-batch instead of the whole training set... ')
            test_gradient(model, training_batch, wd_coefficient)

    if do_early_stopping:
        print('Early stopping: validation loss was lowest after {} iterations. We chose the model that we had then.\n'.format(best_so_far['after_n_iters']))
        theta = best_so_far['theta']

    # the optimization is finished. Now do some reporting.
    model = theta_to_model(theta)
    if n_iters != 0:
        ax = plt.figure(1, figsize=(15,10))
        plt.plot(training_data_losses, 'b')
        plt.plot(validation_data_losses, 'r')
        plt.tick_params(labelsize=25)
        ax.legend(('training', 'validation'), fontsize=25)
        plt.ylabel('loss', fontsize=25);
        plt.xlabel('iteration number', fontsize=25);
        plt.show()

    datas2 = [datas['train'], datas['val'], datas['test']]
    data_names = ['training', 'validation', 'test'];
    for data_i in range(3):
```

```
        data = datas2[data_i]
        data_name = data_names[data_i]
        print('\nThe total loss on the {} data is {}\n'.format(data_name,␣
↪loss(model, data, wd_coefficient)))
        print('The classification loss (i.e. without weight decay) on the {}␣
↪data is {}\n'.format(data_name, loss(model, data, 0)));
        print('The classification error rate on the {} data is {}\n'.
↪format(data_name, classification_performance(model, data)))
```

[6]:
```
# Start training the neural network
#a2(0, 10, 70, 20.0, 0, False, 4)
a2(0, 10, 30, 0.01, 0, False, 10)
```

```
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 3 optimization iterations, training data loss is 2.3025673934869757, and
validation data loss is 2.3025008278520307

After 6 optimization iterations, training data loss is 2.3024876530303207, and
validation data loss is 2.3024208773255115

After 9 optimization iterations, training data loss is 2.3024106986962787, and
validation data loss is 2.302340149057484

After 12 optimization iterations, training data loss is 2.3023537336404405, and
validation data loss is 2.3022851476944663

After 15 optimization iterations, training data loss is 2.3022741261667745, and
validation data loss is 2.302203842915163

After 18 optimization iterations, training data loss is 2.302192586688048, and
validation data loss is 2.3021225988199605

After 21 optimization iterations, training data loss is 2.3020990682386935, and
validation data loss is 2.3020321098244865

After 24 optimization iterations, training data loss is 2.302035768066352, and
validation data loss is 2.301967233398054
```

```
After 27 optimization iterations, training data loss is 2.301958598374691, and
validation data loss is 2.301891225388429

After 30 optimization iterations, training data loss is 2.301906765216956, and
validation data loss is 2.301840691197619

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).
```




```
The total loss on the training data is 2.301906765216956

The classification loss (i.e. without weight decay) on the training data is
2.301906765216956

The classification error rate on the training data is 0.889
```

```
The total loss on the validation data is 2.301840691197619

The classification loss (i.e. without weight decay) on the validation data is
2.301840691197619

The classification error rate on the validation data is 0.895


The total loss on the test data is 2.3018651012099185

The classification loss (i.e. without weight decay) on the test data is
2.3018651012099185

The classification error rate on the test data is 0.8873333333333333
```

When you have completed the programming part, run a2(0, 10, 30, 0.01, 0, False, 10) and report the resulting training data classification loss here:

Training data classification loss: 2.3019

1.3 Exercise 3 - Optimisation using backpropagation

Do Part 3 of the assignment as described at http://www.cs.toronto.edu/~tijmen/csc321/assignments/a2/

The task is to experiment with the example code given above and report your findings. There is no need to program anything in this part but completing it requires that Part 2 is successfully solved.

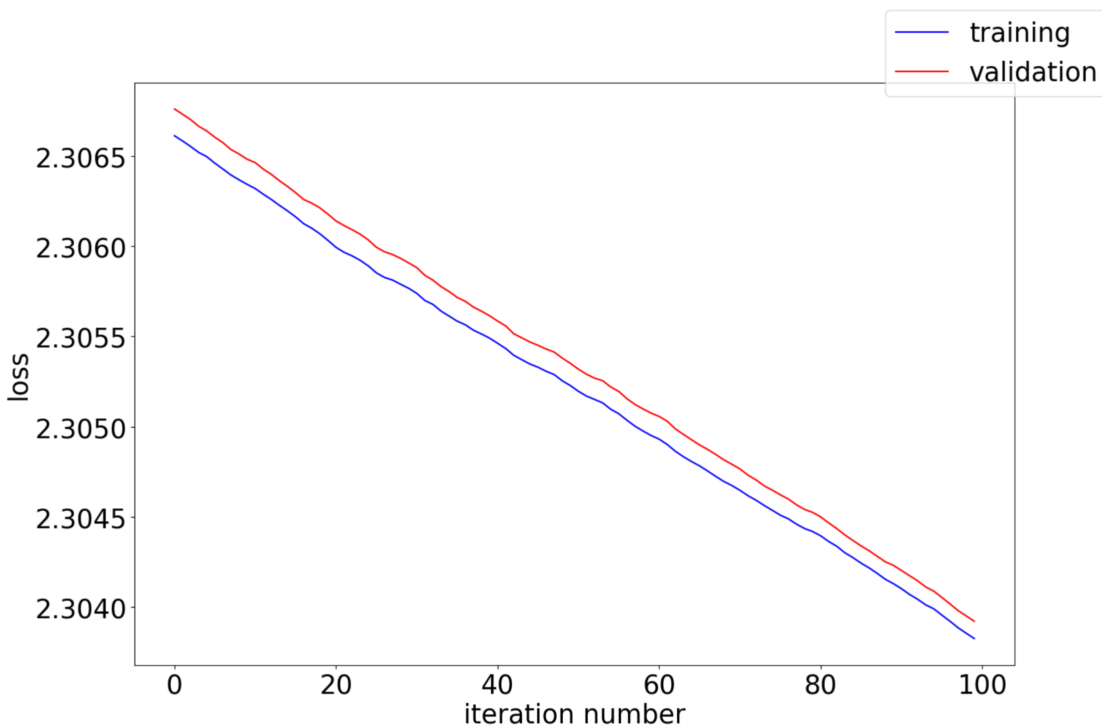
From the tested learning rates and momentum multipliers combinations (as available in the next cell), it is clear that with higher values of momentum multiplier validation and training loses become much more close together, while reaching noticeably lower loss values. Higher learning rates seem to also achieve better results with less loss, though this might mean overfitting - so caution is to be expected in a real case scenario. Interestingly, however, there seems to be a turning point at learning rates with values of 1 and above, where loss reduction seems not to be guaranteed for higher iteration numbers. This caothic behaviour seems to increase with even higher learning rates and for the extreme case of 20, loss actually skyrockets to values not seen before.

[7]:
```python
#try with learning_rate = 0.002, 0.01, 0.05, 0.2, 1.0, 5.0, and 20.0, and with and without momentum_multiplier=0.9

learning_rates = [0.002, 0.01, 0.05, 0.2, 1.0, 5.0, 20.0]
momentum_multipliers = [0, 0.9]

for lr in learning_rates:
    for momentum in momentum_multipliers:
        print(f"\nRunning a2 with learning_rate={lr} and momentum_multiplier={momentum}")
        a2(
            wd_coefficient=0.0001,
```

```
            n_hid=50,
            n_iters=100,
            learning_rate=lr,
            momentum_multiplier=momentum,
            do_early_stopping=True,
            mini_batch_size=10
        )
```

```
Running a2 with learning_rate=0.002 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.3063440436384024, and
validation data loss is 2.3064837343417373

After 20 optimization iterations, training data loss is 2.306033128017481, and
validation data loss is 2.3061787147136896

After 30 optimization iterations, training data loss is 2.3057670884085852, and
validation data loss is 2.3059081054176684

After 40 optimization iterations, training data loss is 2.305490891725173, and
validation data loss is 2.3056149820655625

After 50 optimization iterations, training data loss is 2.305227639709023, and
validation data loss is 2.3053511368166038

After 60 optimization iterations, training data loss is 2.304950681566603, and
validation data loss is 2.305074807026085

After 70 optimization iterations, training data loss is 2.3046727902820163, and
validation data loss is 2.3047908319330097

After 80 optimization iterations, training data loss is 2.3044176321175804, and
validation data loss is 2.30452393833895

After 90 optimization iterations, training data loss is 2.3041282477926464, and
validation data loss is 2.304229837395

After 100 optimization iterations, training data loss is 2.303824231100317, and
validation data loss is 2.3039202732849087
```

```
Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the
model that we had then.
```




```
The total loss on the training data is 2.303824231100317

The classification loss (i.e. without weight decay) on the training data is
2.3004991010430778

The classification error rate on the training data is 0.9


The total loss on the validation data is 2.3039202732849087
```

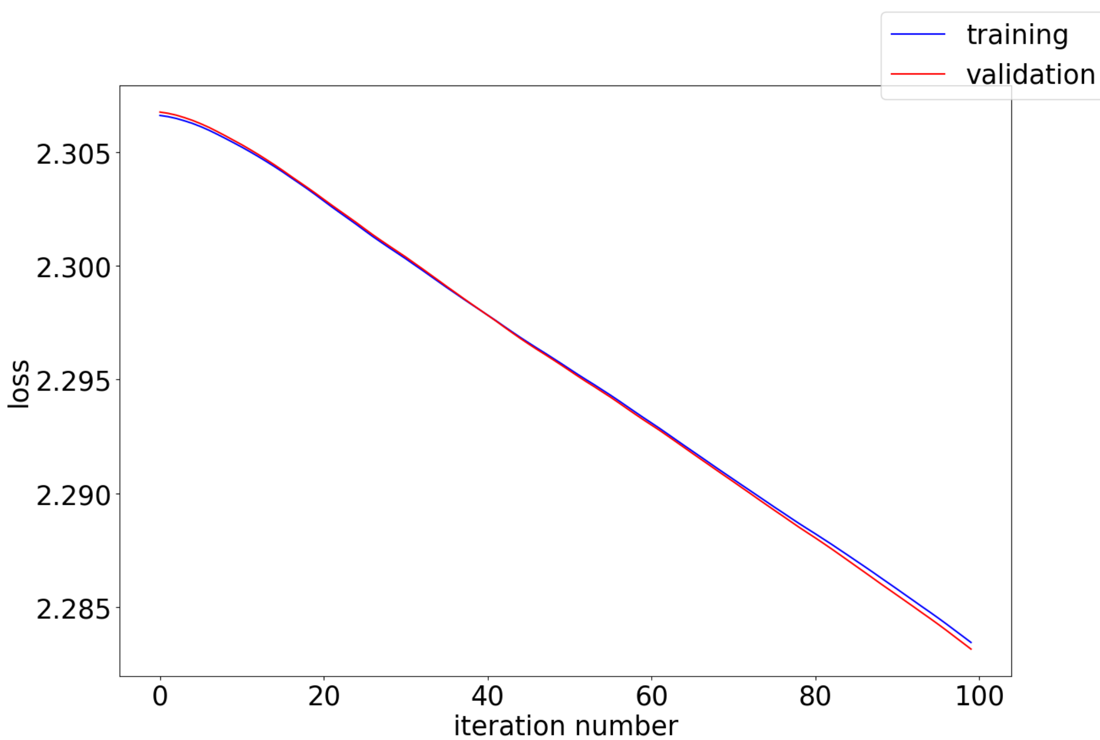
```
The classification loss (i.e. without weight decay) on the validation data is
2.3005951432276692

The classification error rate on the validation data is 0.9


The total loss on the test data is 2.3035910482429216

The classification loss (i.e. without weight decay) on the test data is
2.300265918185682

The classification error rate on the test data is 0.9001111111111111


Running a2 with learning_rate=0.002 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.3054108397815956, and
validation data loss is 2.30551791131349

After 20 optimization iterations, training data loss is 2.303122415002489, and
validation data loss is 2.303186521743964

After 30 optimization iterations, training data loss is 2.300552583048394, and
validation data loss is 2.300629006235988

After 40 optimization iterations, training data loss is 2.2980737430658733, and
validation data loss is 2.2980791031690204

After 50 optimization iterations, training data loss is 2.295701058751779, and
validation data loss is 2.2956343872409266

After 60 optimization iterations, training data loss is 2.2933299019759383, and
validation data loss is 2.293235079095429

After 70 optimization iterations, training data loss is 2.290858307722431, and
validation data loss is 2.290754021422712

After 80 optimization iterations, training data loss is 2.2884452107817705, and
validation data loss is 2.2882724705376685
```

After 90 optimization iterations, training data loss is 2.2860324705801247, and validation data loss is 2.2857658457046286

After 100 optimization iterations, training data loss is 2.2834414901431774, and validation data loss is 2.2831495102949693

Now testing the gradient on just a mini-batch instead of the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the model that we had then.



The total loss on the training data is 2.2834414901431774

The classification loss (i.e. without weight decay) on the training data is 2.2801139954809306

The classification error rate on the training data is 0.708

The total loss on the validation data is 2.2831495102949693

The classification loss (i.e. without weight decay) on the validation data is 2.2798220156327225

The classification error rate on the validation data is 0.714

The total loss on the test data is 2.2831691604242272

The classification loss (i.e. without weight decay) on the test data is 2.2798416657619804

The classification error rate on the test data is 0.725

Running a2 with learning_rate=0.01 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).

After 10 optimization iterations, training data loss is 2.305175352397671, and validation data loss is 2.305271234341097

After 20 optimization iterations, training data loss is 2.303681112977955, and validation data loss is 2.3038075227609687

After 30 optimization iterations, training data loss is 2.302430765027475, and validation data loss is 2.3025355228600426

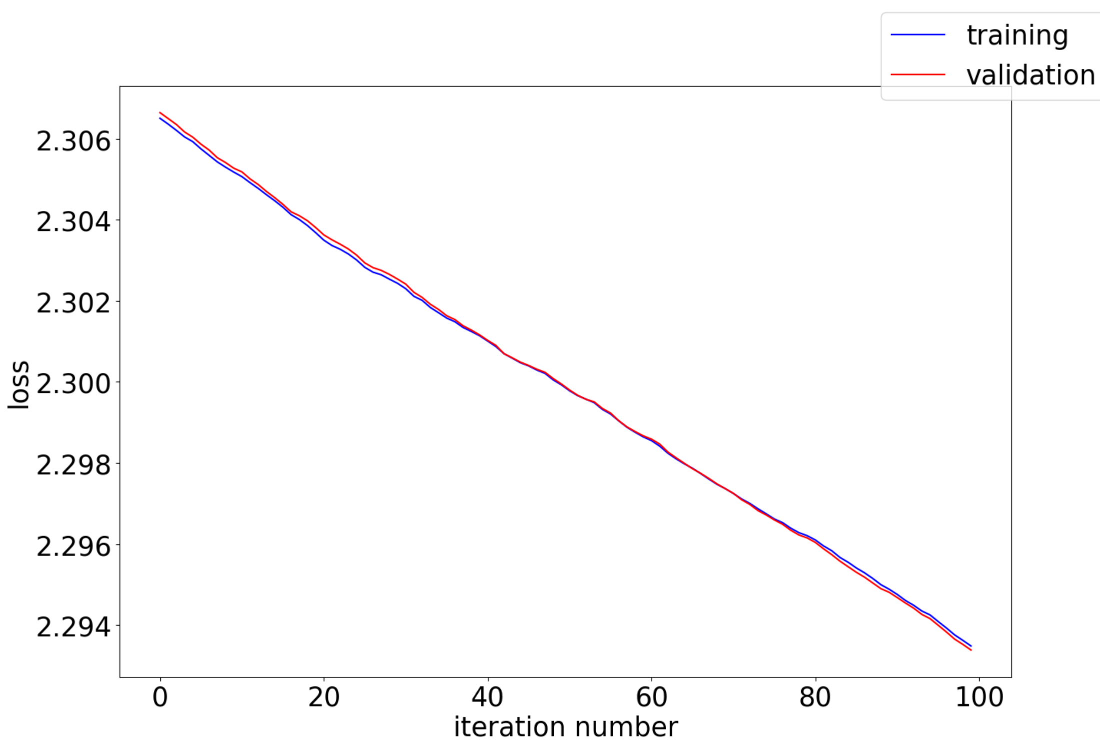
After 40 optimization iterations, training data loss is 2.301139043806984, and validation data loss is 2.3011608811614024

After 50 optimization iterations, training data loss is 2.299926123058619, and validation data loss is 2.2999472797089076

After 60 optimization iterations, training data loss is 2.298641700411486, and validation data loss is 2.2986682681347856

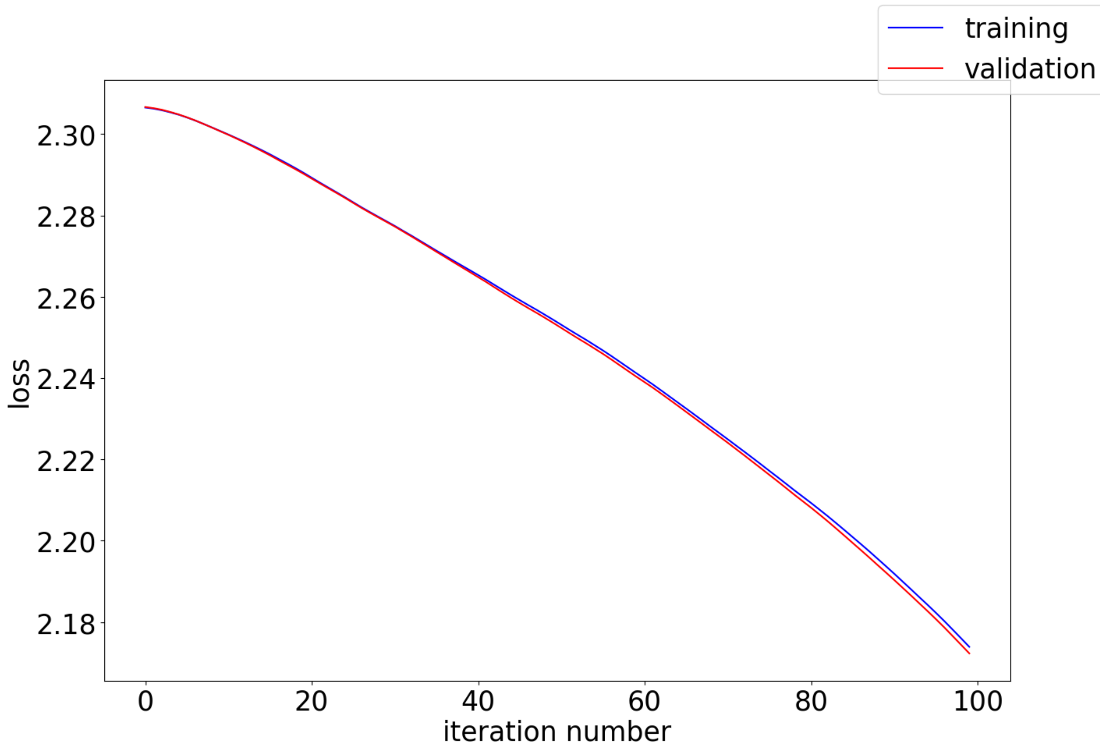
After 70 optimization iterations, training data loss is 2.2973665693945984, and

```
validation data loss is 2.2973663590747577

After 80 optimization iterations, training data loss is 2.296205388891933, and
validation data loss is 2.2961497454816806

After 90 optimization iterations, training data loss is 2.2948853730119425, and
validation data loss is 2.2948098961997307

After 100 optimization iterations, training data loss is 2.2934844555797995, and
validation data loss is 2.293385070358592

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the
model that we had then.
```



```
The total loss on the training data is 2.2934844555797995

The classification loss (i.e. without weight decay) on the training data is
2.290158745724578

The classification error rate on the training data is 0.754


The total loss on the validation data is 2.293385070358592

The classification loss (i.e. without weight decay) on the validation data is
2.2900593605033706

The classification error rate on the validation data is 0.764


The total loss on the test data is 2.2932241084418026

The classification loss (i.e. without weight decay) on the test data is
2.289898398586581

The classification error rate on the test data is 0.7566666666666667


Running a2 with learning_rate=0.01 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.3007415713094237, and
validation data loss is 2.30067807757045

After 20 optimization iterations, training data loss is 2.2904813098655423, and
validation data loss is 2.290233683858559

After 30 optimization iterations, training data loss is 2.2785154572015944, and
validation data loss is 2.278360848071391

After 40 optimization iterations, training data loss is 2.2665081446384994, and
validation data loss is 2.266049950263822

After 50 optimization iterations, training data loss is 2.25433959560252, and
validation data loss is 2.253573486059632
```

```
After 60 optimization iterations, training data loss is 2.2411839871760506, and
validation data loss is 2.2403310569858794

After 70 optimization iterations, training data loss is 2.2264260150994115, and
validation data loss is 2.2255783735282444

After 80 optimization iterations, training data loss is 2.210824389680021, and
validation data loss is 2.209698700252539

After 90 optimization iterations, training data loss is 2.193709503680815, and
validation data loss is 2.192159239485517

After 100 optimization iterations, training data loss is 2.1739127593836005, and
validation data loss is 2.1723058235442716

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the
model that we had then.
```



The total loss on the training data is 2.1739127593836005

The classification loss (i.e. without weight decay) on the training data is 2.170504104595808

The classification error rate on the training data is 0.669

The total loss on the validation data is 2.1723058235442716

The classification loss (i.e. without weight decay) on the validation data is 2.168897168756479

The classification error rate on the validation data is 0.67

The total loss on the test data is 2.1731866786892096

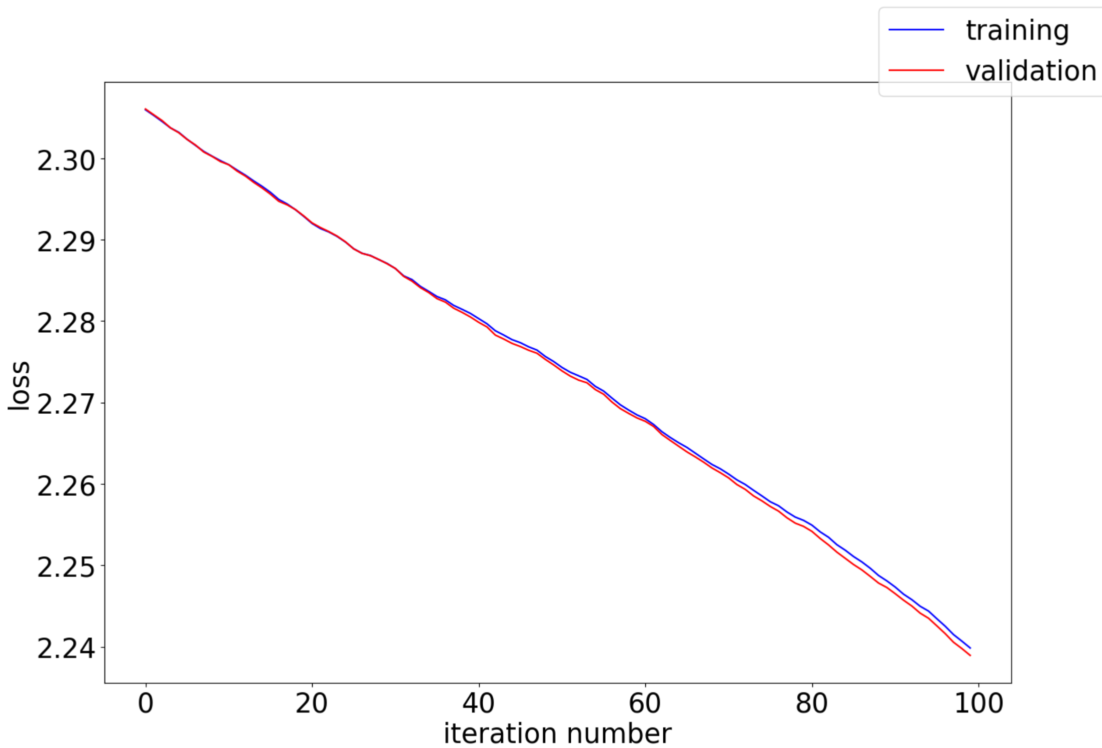
The classification loss (i.e. without weight decay) on the test data is 2.169778023901417

The classification error rate on the test data is 0.6816666666666666

```
Running a2 with learning_rate=0.05 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.299700554436991, and
validation data loss is 2.2995873352979794

After 20 optimization iterations, training data loss is 2.2928570664979753, and
validation data loss is 2.2929123922716466

After 30 optimization iterations, training data loss is 2.2870808288086613, and
validation data loss is 2.28704105724505

After 40 optimization iterations, training data loss is 2.280939787078889, and
validation data loss is 2.2805052402567916

After 50 optimization iterations, training data loss is 2.275028451225197, and
validation data loss is 2.2746108079562903

After 60 optimization iterations, training data loss is 2.268472928986622, and
validation data loss is 2.2681029775603365

After 70 optimization iterations, training data loss is 2.261855084332333, and
validation data loss is 2.2613742570733493

After 80 optimization iterations, training data loss is 2.2555163194102184, and
validation data loss is 2.2547785974504975

After 90 optimization iterations, training data loss is 2.2480834458512047, and
validation data loss is 2.2472696104848016

After 100 optimization iterations, training data loss is 2.2398476108370904, and
validation data loss is 2.2389362070994774

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
```

certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the model that we had then.



The total loss on the training data is 2.2398476108370904

The classification loss (i.e. without weight decay) on the training data is 2.2364962971699667

The classification error rate on the training data is 0.681

The total loss on the validation data is 2.2389362070994774

The classification loss (i.e. without weight decay) on the validation data is 2.2355848934323537

The classification error rate on the validation data is 0.694

The total loss on the test data is 2.2394256539342536

The classification loss (i.e. without weight decay) on the test data is
2.23607434026713

The classification error rate on the test data is 0.7025555555555556

Running a2 with learning_rate=0.05 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).

After 10 optimization iterations, training data loss is 2.2798046221327706, and validation data loss is 2.2789566441674425

After 20 optimization iterations, training data loss is 2.2282314314508422, and validation data loss is 2.226710586929939

After 30 optimization iterations, training data loss is 2.151147110673753, and validation data loss is 2.1503513786954613

After 40 optimization iterations, training data loss is 2.0488342388660166, and validation data loss is 2.0474914714171084

After 50 optimization iterations, training data loss is 1.9229071136007856, and validation data loss is 1.9218297060634912

After 60 optimization iterations, training data loss is 1.791952787358903, and validation data loss is 1.793336357532944

After 70 optimization iterations, training data loss is 1.6675359179812643, and validation data loss is 1.6723739679508398

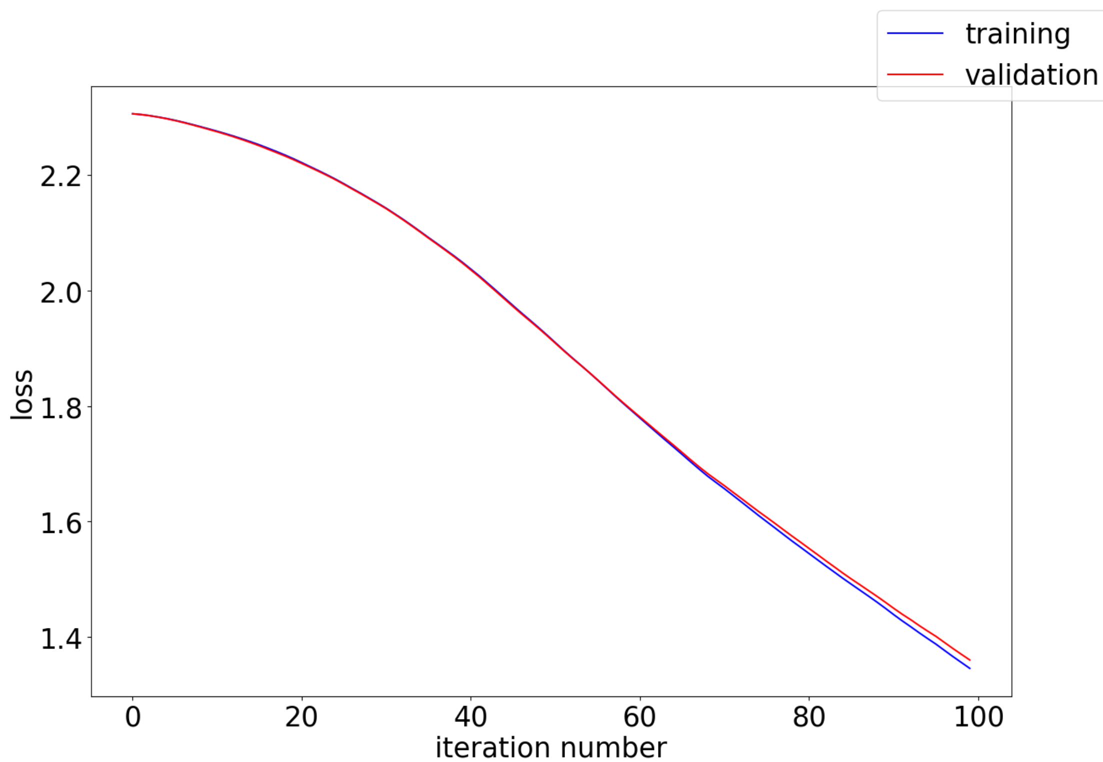
After 80 optimization iterations, training data loss is 1.5553156163598594, and validation data loss is 1.5641003239519051

After 90 optimization iterations, training data loss is 1.4499960713311624, and validation data loss is 1.4604102470029923

After 100 optimization iterations, training data loss is 1.3457837551756977, and validation data loss is 1.3603344989343396

Now testing the gradient on just a mini-batch instead of the whole training set…

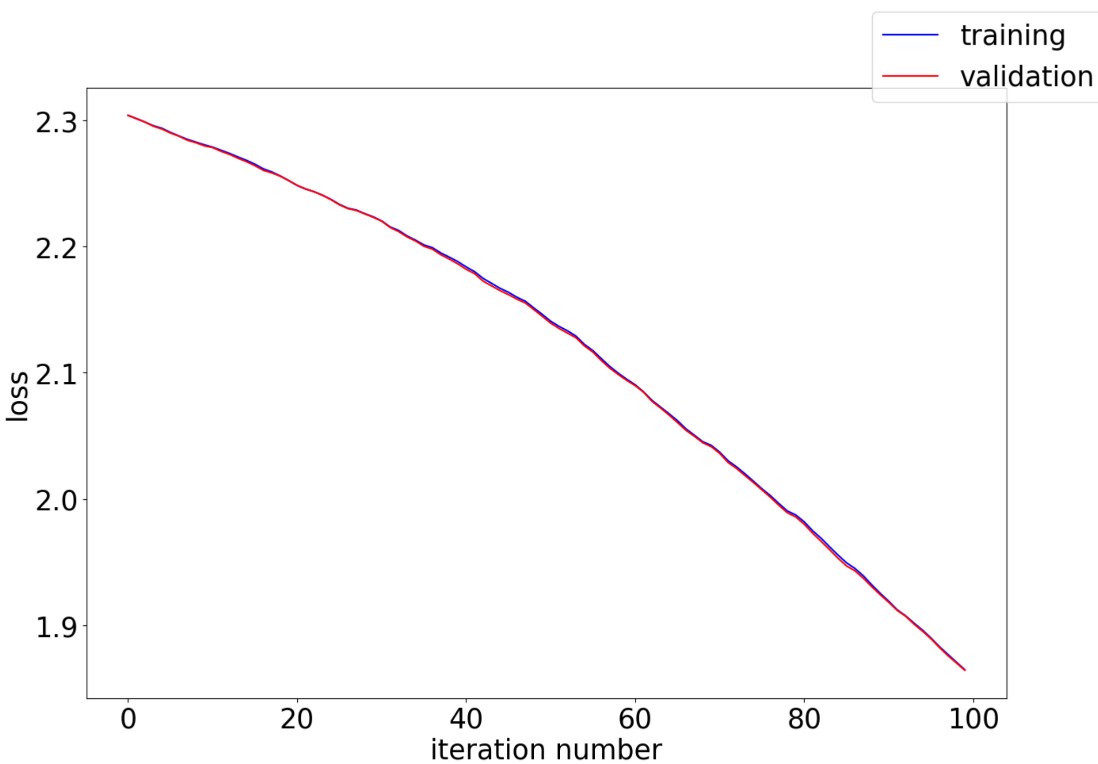
```
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the
model that we had then.
```




```
The total loss on the training data is 1.3457837551756977

The classification loss (i.e. without weight decay) on the training data is
1.3403030616038065

The classification error rate on the training data is 0.396


The total loss on the validation data is 1.3603344989343396

The classification loss (i.e. without weight decay) on the validation data is
```

```
1.3548538053624484

The classification error rate on the validation data is 0.409


The total loss on the test data is 1.3435354670895752

The classification loss (i.e. without weight decay) on the test data is
1.338054773517684

The classification error rate on the test data is 0.405


Running a2 with learning_rate=0.2 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.280649227960419, and
validation data loss is 2.2798203656231806

After 20 optimization iterations, training data loss is 2.2522955910059963, and
validation data loss is 2.2522123662333446

After 30 optimization iterations, training data loss is 2.223563088423211, and
validation data loss is 2.223158231765997

After 40 optimization iterations, training data loss is 2.188050742746847, and
validation data loss is 2.186271040059622

After 50 optimization iterations, training data loss is 2.1462364916719583, and
validation data loss is 2.1446791028721655

After 60 optimization iterations, training data loss is 2.0948146586447534, and
validation data loss is 2.09388477360718

After 70 optimization iterations, training data loss is 2.042456218366792, and
validation data loss is 2.041368128569927

After 80 optimization iterations, training data loss is 1.987259312267679, and
validation data loss is 1.9856776141237753

After 90 optimization iterations, training data loss is 1.925126628793607, and
validation data loss is 1.9240008345950546
```

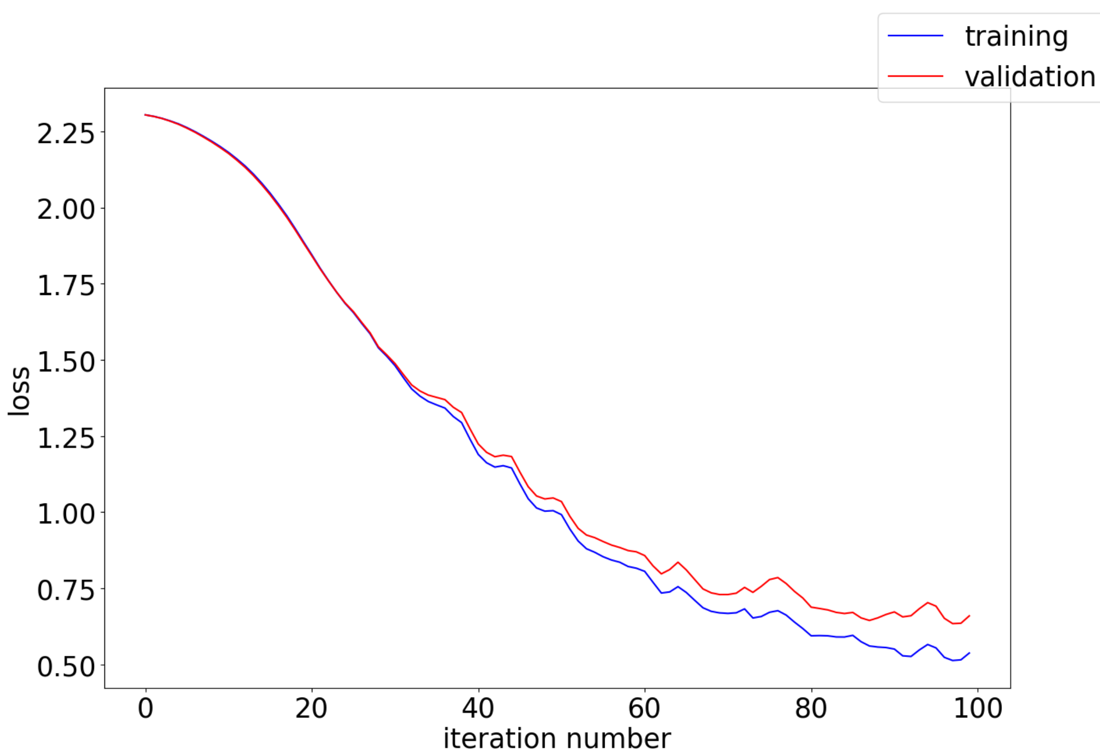
```
After 100 optimization iterations, training data loss is 1.8646370611512482, and
validation data loss is 1.8641993127247702

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 100 iterations. We chose the
model that we had then.
```




```
The total loss on the training data is 1.8646370611512482

The classification loss (i.e. without weight decay) on the training data is
1.8607716244617327
```

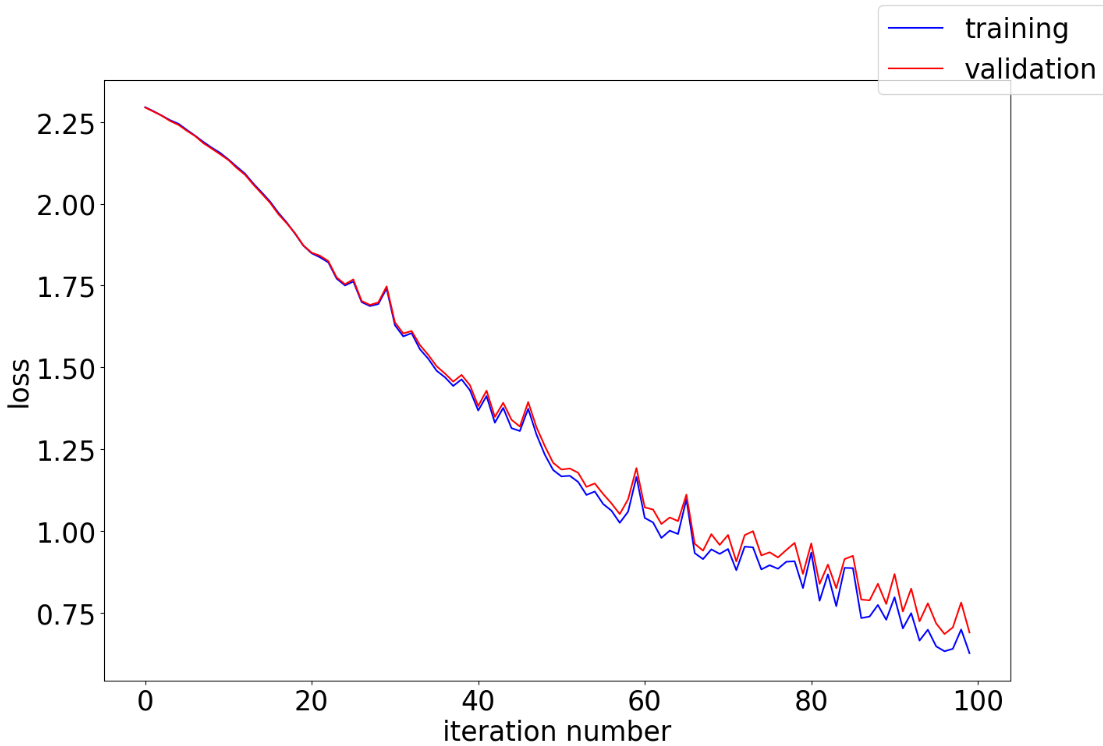
```
The classification error rate on the training data is 0.581


The total loss on the validation data is 1.8641993127247702

The classification loss (i.e. without weight decay) on the validation data is
1.8603338760352548

The classification error rate on the validation data is 0.585


The total loss on the test data is 1.8599894237172148

The classification loss (i.e. without weight decay) on the test data is
1.8561239870276993

The classification error rate on the test data is 0.5848888888888889


Running a2 with learning_rate=0.2 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.199808508112593, and
validation data loss is 2.196355018070401

After 20 optimization iterations, training data loss is 1.88751458816891, and
validation data loss is 1.8835386009442392

After 30 optimization iterations, training data loss is 1.5119754224917568, and
validation data loss is 1.5165086631961295

After 40 optimization iterations, training data loss is 1.2402440286905247, and
validation data loss is 1.2741486236876052

After 50 optimization iterations, training data loss is 1.0050199630786516, and
validation data loss is 1.0467648632561193

After 60 optimization iterations, training data loss is 0.8161635619143874, and
validation data loss is 0.8699222216174478

After 70 optimization iterations, training data loss is 0.6695846497354878, and
validation data loss is 0.7297564260196184
```

```
After 80 optimization iterations, training data loss is 0.6181113935553104, and
validation data loss is 0.7183306988818965

After 90 optimization iterations, training data loss is 0.5558518315032634, and
validation data loss is 0.6644510162451877

After 100 optimization iterations, training data loss is 0.5378352432084349, and
validation data loss is 0.6597797735546233

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 98 iterations. We chose the
model that we had then.
```



```
The total loss on the training data is 0.5132863629302705

The classification loss (i.e. without weight decay) on the training data is
0.49688709332161807

The classification error rate on the training data is 0.165


The total loss on the validation data is 0.6344054218171142

The classification loss (i.e. without weight decay) on the validation data is
0.6180061522084618

The classification error rate on the validation data is 0.203


The total loss on the test data is 0.6076288834957079

The classification loss (i.e. without weight decay) on the test data is
0.5912296138870554

The classification error rate on the test data is 0.189


Running a2 with learning_rate=1.0 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.155767485734512, and
validation data loss is 2.1514579850427107

After 20 optimization iterations, training data loss is 1.8721150102622304, and
validation data loss is 1.872813188008605

After 30 optimization iterations, training data loss is 1.7412484587727746, and
validation data loss is 1.7476091877986244

After 40 optimization iterations, training data loss is 1.430375782399413, and
validation data loss is 1.4458725533432375

After 50 optimization iterations, training data loss is 1.186264195675582, and
validation data loss is 1.2083504289727698
```

```
After 60 optimization iterations, training data loss is 1.1652285419375263, and
validation data loss is 1.1921859904788936

After 70 optimization iterations, training data loss is 0.9299719309989601, and
validation data loss is 0.957330225090055

After 80 optimization iterations, training data loss is 0.8255607967119267, and
validation data loss is 0.8689616957682886

After 90 optimization iterations, training data loss is 0.7286975079751447, and
validation data loss is 0.776814387408782

After 100 optimization iterations, training data loss is 0.6264728835851786, and
validation data loss is 0.689793531349423

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 97 iterations. We chose the
model that we had then.
```



The total loss on the training data is 0.6323794683623022

The classification loss (i.e. without weight decay) on the training data is 0.6223404731314566

The classification error rate on the training data is 0.179

The total loss on the validation data is 0.6850964276763187

The classification loss (i.e. without weight decay) on the validation data is 0.6750574324454731

The classification error rate on the validation data is 0.206

The total loss on the test data is 0.667375932554453

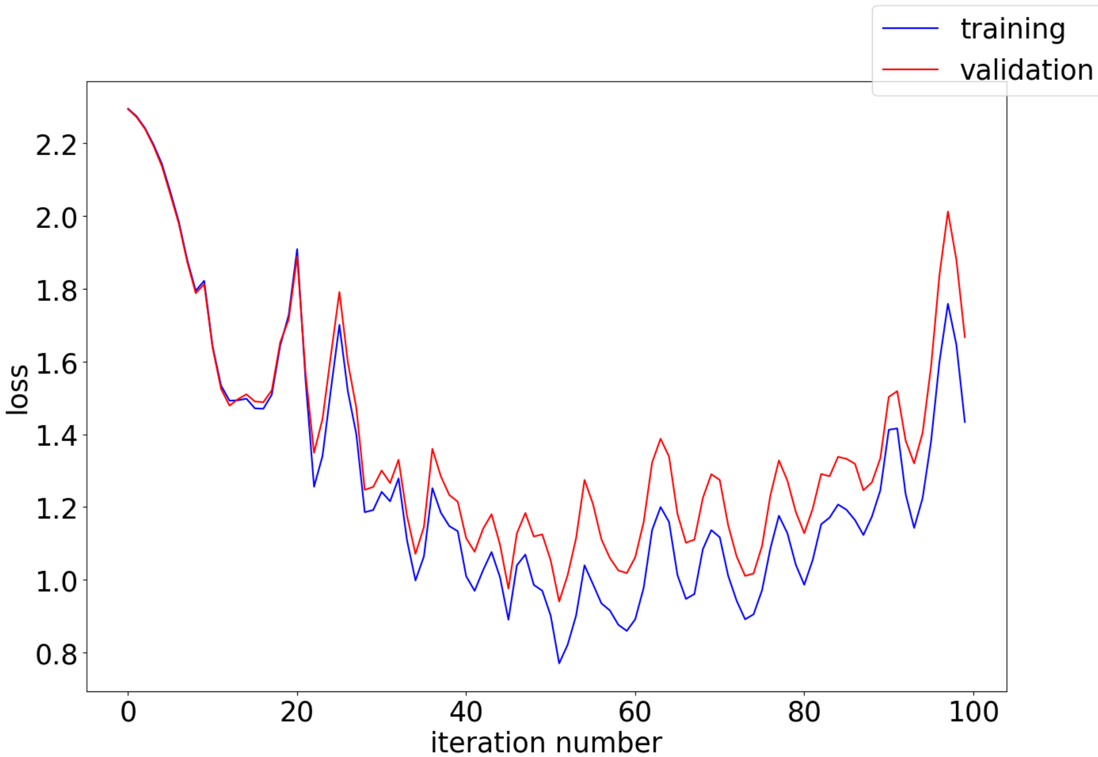
The classification loss (i.e. without weight decay) on the test data is 0.6573369373236074

The classification error rate on the test data is 0.19488888888888889

```
Running a2 with learning_rate=1.0 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 1.8222595228080707, and
validation data loss is 1.812987023113807

After 20 optimization iterations, training data loss is 1.727847877793427, and
validation data loss is 1.7158318938332817

After 30 optimization iterations, training data loss is 1.1919182254059988, and
validation data loss is 1.2553566422436562

After 40 optimization iterations, training data loss is 1.1337390141845989, and
validation data loss is 1.2148790887168752

After 50 optimization iterations, training data loss is 0.9701340161687102, and
validation data loss is 1.1249793804461492

After 60 optimization iterations, training data loss is 0.8595973566913905, and
validation data loss is 1.0184792757594678

After 70 optimization iterations, training data loss is 1.136733273786287, and
validation data loss is 1.2903661010917749

After 80 optimization iterations, training data loss is 1.0414152309317903, and
validation data loss is 1.1867617632533465

After 90 optimization iterations, training data loss is 1.2460658779888427, and
validation data loss is 1.334105214808347

After 100 optimization iterations, training data loss is 1.4339526428218332, and
validation data loss is 1.667156367456518

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
```

certainly, but probably).

Early stopping: validation loss was lowest after 52 iterations. We chose the model that we had then.



The total loss on the training data is 0.7703126098283415

The classification loss (i.e. without weight decay) on the training data is 0.6616052581467627

The classification error rate on the training data is 0.22

The total loss on the validation data is 0.940396012254018

The classification loss (i.e. without weight decay) on the validation data is 0.8316886605724393

The classification error rate on the validation data is 0.251

The total loss on the test data is 0.8775824683623481

The classification loss (i.e. without weight decay) on the test data is 0.7688751166807694

The classification error rate on the test data is 0.2528888888888889

Running a2 with learning_rate=5.0 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).

After 10 optimization iterations, training data loss is 2.2159679891723227, and validation data loss is 2.2229272430218776

After 20 optimization iterations, training data loss is 2.007802463986861, and validation data loss is 2.012974804815143

After 30 optimization iterations, training data loss is 1.8301693715037803, and validation data loss is 1.827645339036513

After 40 optimization iterations, training data loss is 1.2621564710643407, and validation data loss is 1.2875704897798779

After 50 optimization iterations, training data loss is 1.056928253467131, and validation data loss is 1.1336742119760073

After 60 optimization iterations, training data loss is 1.389281154304889, and validation data loss is 1.485251483812934

After 70 optimization iterations, training data loss is 0.9970621831306337, and validation data loss is 1.0479064185990583

After 80 optimization iterations, training data loss is 1.403387227031406, and validation data loss is 1.4706680172520978

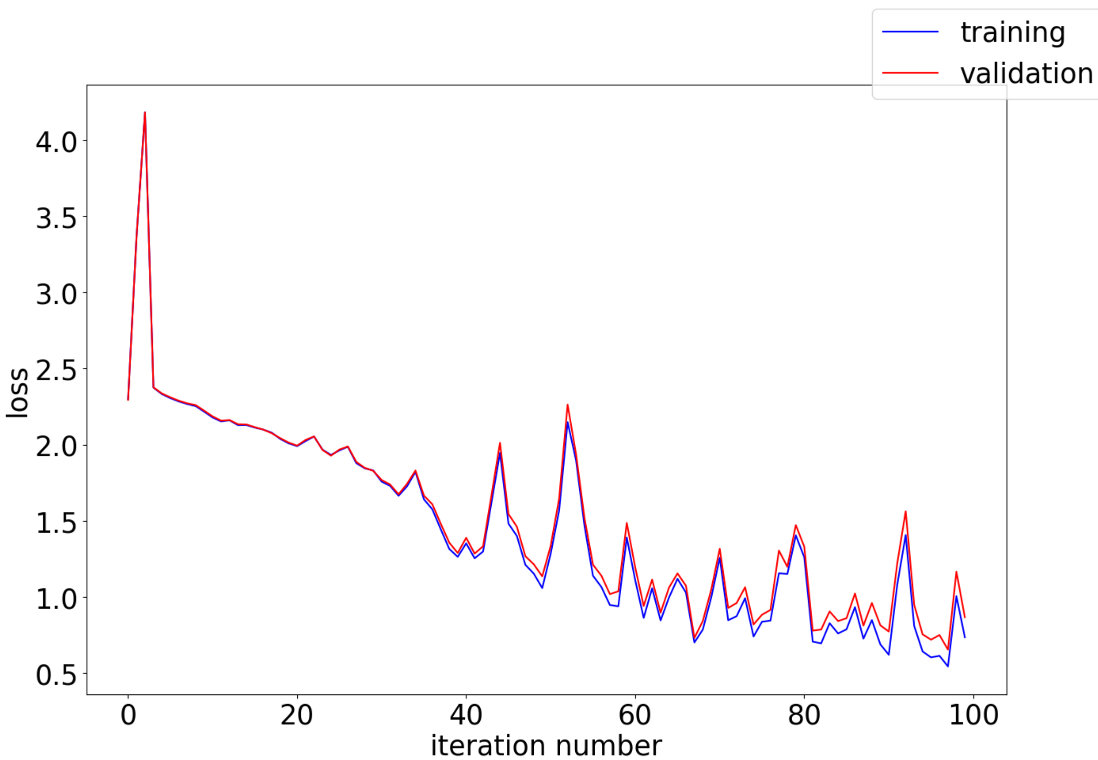
After 90 optimization iterations, training data loss is 0.6872227925901683, and validation data loss is 0.8123449605082234

After 100 optimization iterations, training data loss is 0.7337277761832077, and validation data loss is 0.8653306618131538

Now testing the gradient on just a mini-batch instead of the whole training

set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).

Early stopping: validation loss was lowest after 98 iterations. We chose the model that we had then.



The total loss on the training data is 0.5418927188469397

The classification loss (i.e. without weight decay) on the training data is 0.49045571493018075

The classification error rate on the training data is 0.147

The total loss on the validation data is 0.6524785132202452

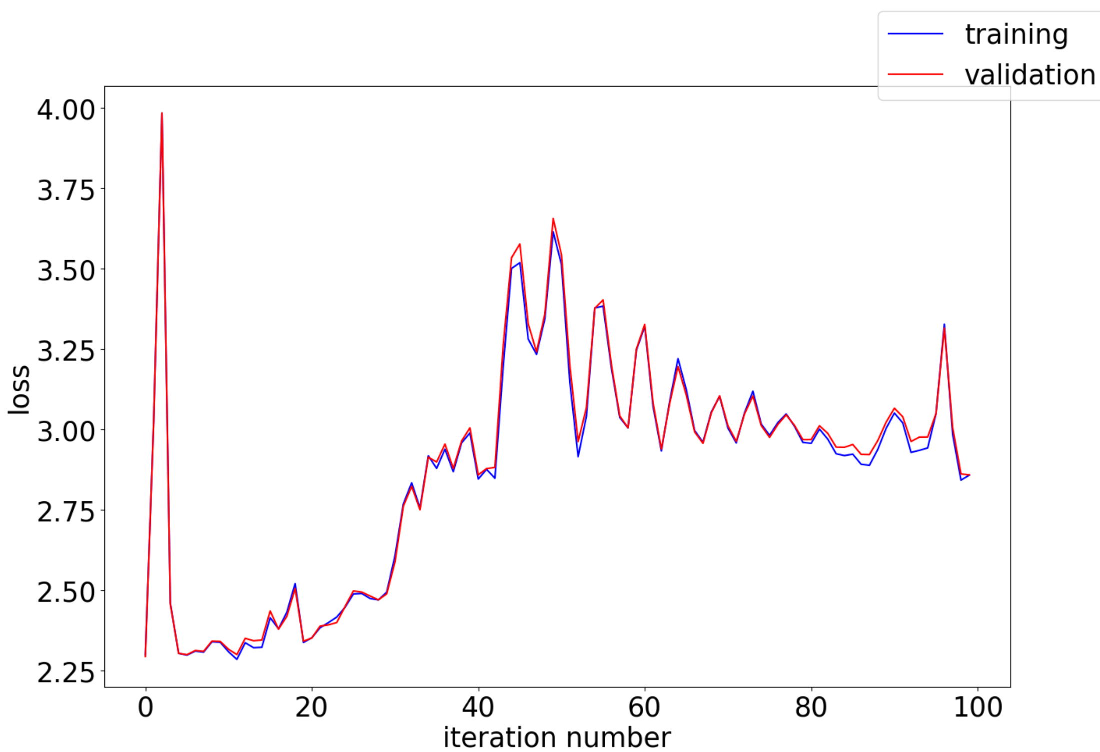
```
The classification loss (i.e. without weight decay) on the validation data is
0.6010415093034862

The classification error rate on the validation data is 0.188


The total loss on the test data is 0.64633131378158

The classification loss (i.e. without weight decay) on the test data is
0.5948943098648211

The classification error rate on the test data is 0.18788888888888888


Running a2 with learning_rate=5.0 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.3384388195613015, and
validation data loss is 2.3411453367491153

After 20 optimization iterations, training data loss is 2.3378915037048196, and
validation data loss is 2.3418493588034437

After 30 optimization iterations, training data loss is 2.494260350067743, and
validation data loss is 2.4888976083359458

After 40 optimization iterations, training data loss is 2.98899104725451, and
validation data loss is 3.0048454134420464

After 50 optimization iterations, training data loss is 3.6147499137703782, and
validation data loss is 3.65602945353365

After 60 optimization iterations, training data loss is 3.246131916476843, and
validation data loss is 3.249837994337108

After 70 optimization iterations, training data loss is 3.102798555866264, and
validation data loss is 3.1044266282014235

After 80 optimization iterations, training data loss is 2.9599267698970686, and
validation data loss is 2.9683908200241835

After 90 optimization iterations, training data loss is 3.002965992053498, and
```

validation data loss is 3.022249946176657

After 100 optimization iterations, training data loss is 2.8578594758250833, and validation data loss is 2.858933891669286

Now testing the gradient on just a mini-batch instead of the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is within 0.001%% of the gradient that the finite difference approximation computed, so the gradient calculation procedure is probably correct (not certainly, but probably).

Early stopping: validation loss was lowest after 1 iterations. We chose the model that we had then.

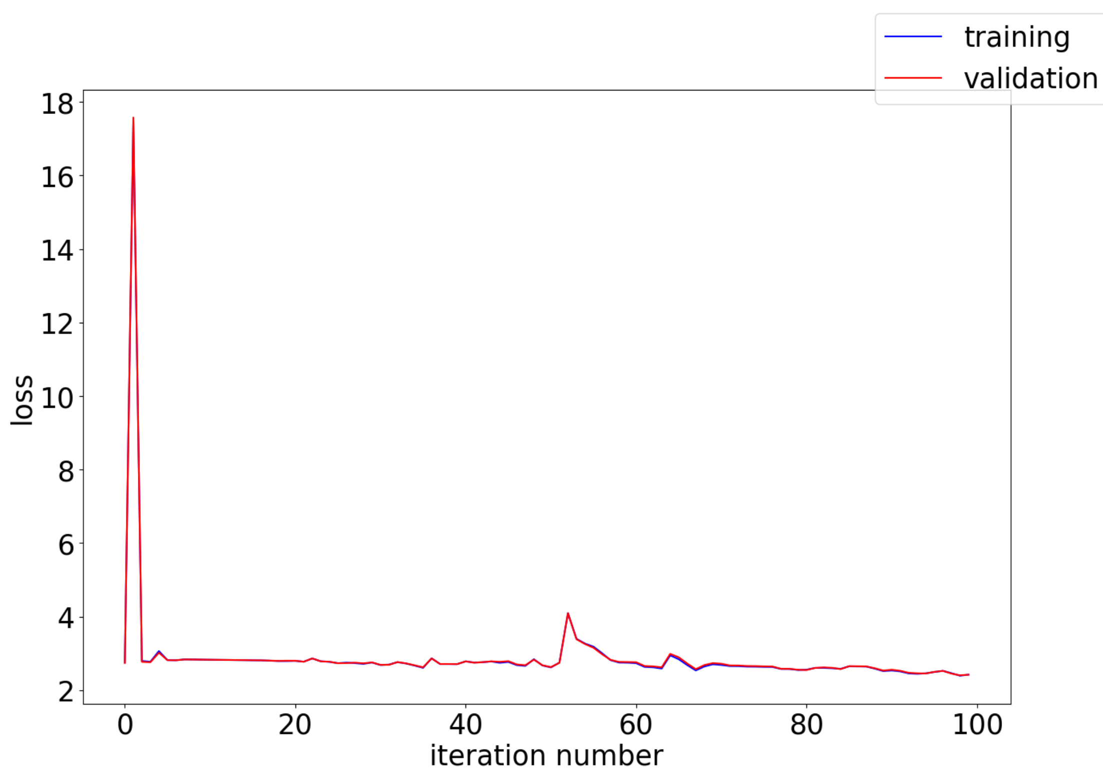


The total loss on the training data is 2.299739692206897

The classification loss (i.e. without weight decay) on the training data is 2.296311579583822

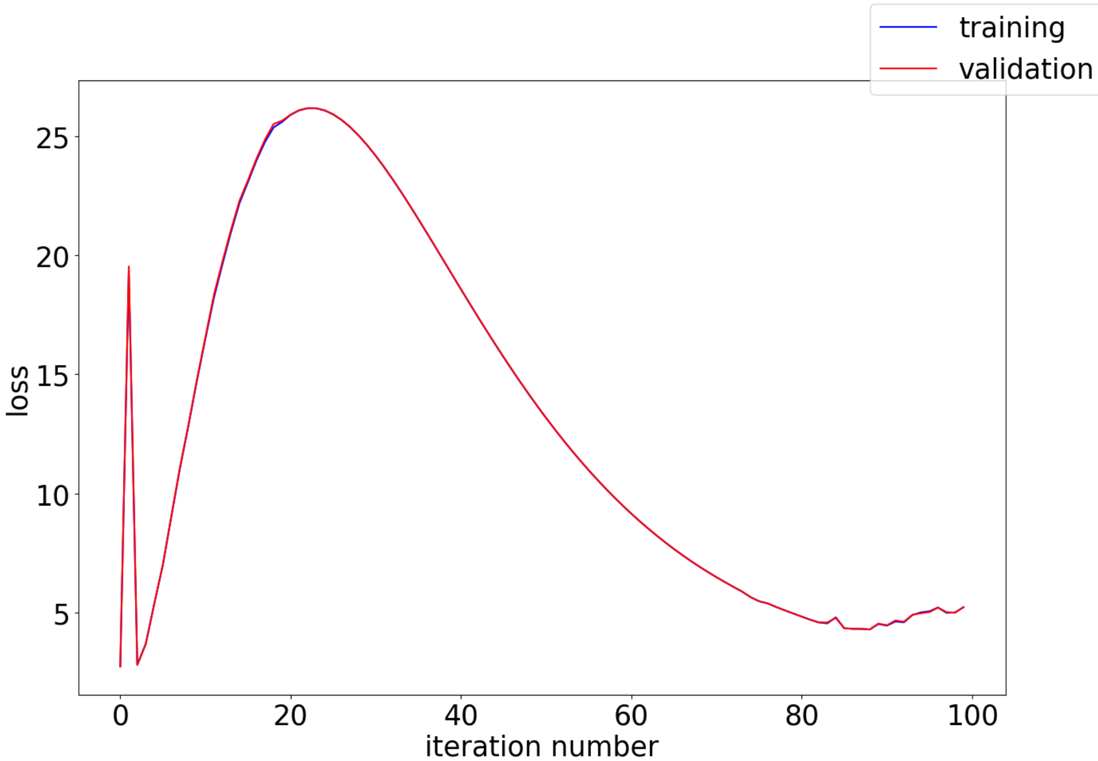
```
The classification error rate on the training data is 0.92


The total loss on the validation data is 2.2940845725217844

The classification loss (i.e. without weight decay) on the validation data is
2.2906564598987096

The classification error rate on the validation data is 0.919


The total loss on the test data is 2.291849734540491

The classification loss (i.e. without weight decay) on the test data is
2.2884216219174163

The classification error rate on the test data is 0.9088888888888889


Running a2 with learning_rate=20.0 and momentum_multiplier=0
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 2.830788969473888, and
validation data loss is 2.8303895650524034

After 20 optimization iterations, training data loss is 2.790517908292589, and
validation data loss is 2.8006989660443087

After 30 optimization iterations, training data loss is 2.7526122476161112, and
validation data loss is 2.7558635388597215

After 40 optimization iterations, training data loss is 2.70933646593866, and
validation data loss is 2.709164404181748

After 50 optimization iterations, training data loss is 2.6734372860044306, and
validation data loss is 2.6779131822437727

After 60 optimization iterations, training data loss is 2.7474369799103298, and
validation data loss is 2.7655958423114777

After 70 optimization iterations, training data loss is 2.7036871854177966, and
validation data loss is 2.7359699447612558
```

```
After 80 optimization iterations, training data loss is 2.548807406969669, and
validation data loss is 2.5564659133532084

After 90 optimization iterations, training data loss is 2.5179348917661106, and
validation data loss is 2.53338354511737

After 100 optimization iterations, training data loss is 2.4216987923946363, and
validation data loss is 2.4202881715016065

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 99 iterations. We chose the
model that we had then.
```



```
The total loss on the training data is 2.3936565787164947

The classification loss (i.e. without weight decay) on the training data is
1.9814185349450568

The classification error rate on the training data is 0.79


The total loss on the validation data is 2.4044134476014536

The classification loss (i.e. without weight decay) on the validation data is
1.992175403830016

The classification error rate on the validation data is 0.807


The total loss on the test data is 2.4117479398976576

The classification loss (i.e. without weight decay) on the test data is
1.9995098961262197

The classification error rate on the test data is 0.7955555555555556


Running a2 with learning_rate=20.0 and momentum_multiplier=0.9
Now testing the gradient on the whole training set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

After 10 optimization iterations, training data loss is 14.738227863951636, and
validation data loss is 14.78653797372617

After 20 optimization iterations, training data loss is 25.594724595876826, and
validation data loss is 25.645662544329625

After 30 optimization iterations, training data loss is 24.61125925968661, and
validation data loss is 24.618860120385396

After 40 optimization iterations, training data loss is 19.158876890063954, and
validation data loss is 19.164724319333807

After 50 optimization iterations, training data loss is 13.650155295156136, and
validation data loss is 13.653945771534412
```

```
After 60 optimization iterations, training data loss is 9.490857356259612, and
validation data loss is 9.492730173046445


/notebooks/ComputerVision/HW9/utils.py:50: RuntimeWarning: overflow encountered
in exp
  ret = 1 / (1 + np.exp(-input))

After 70 optimization iterations, training data loss is 6.704515666209893, and
validation data loss is 6.704870708940403

After 80 optimization iterations, training data loss is 4.969227723579632, and
validation data loss is 4.968880900103409

After 90 optimization iterations, training data loss is 4.526209483094469, and
validation data loss is 4.543935988951166

After 100 optimization iterations, training data loss is 5.230588522945585, and
validation data loss is 5.237759916160097

Now testing the gradient on just a mini-batch instead of the whole training
set…
Gradient test passed for hid_to_class.
Gradient test passed for input_to_hid.
Gradient test passed. That means that the gradient that your code computed is
within 0.001%% of the gradient that the finite difference approximation
computed, so the gradient calculation procedure is probably correct (not
certainly, but probably).

Early stopping: validation loss was lowest after 1 iterations. We chose the
model that we had then.
```




```
The total loss on the training data is 2.758743841110097

The classification loss (i.e. without weight decay) on the training data is
2.753747837714326

The classification error rate on the training data is 0.928


The total loss on the validation data is 2.737106890254882

The classification loss (i.e. without weight decay) on the validation data is
2.732110886859111

The classification error rate on the validation data is 0.926


The total loss on the test data is 2.7338713744875527

The classification loss (i.e. without weight decay) on the test data is
2.7288753710917817

The classification error rate on the test data is 0.9157777777777778
```

```
[ ]:
```