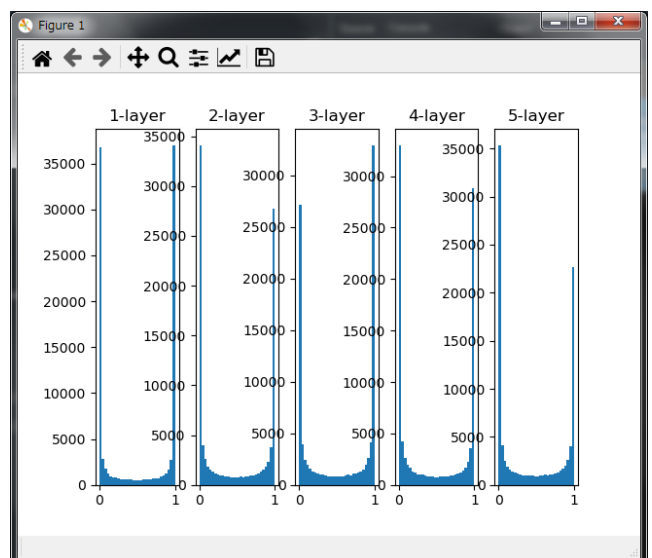
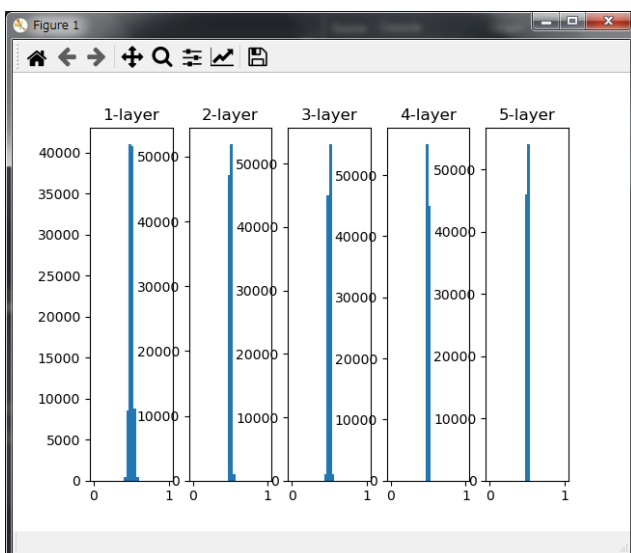


1 Section1_勾配消失問題

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 def sigmoid(x):
5     return 1 / (1 + np.exp(-x))
6
7 x = np.random.randn(1000, 100)
8 node_num = 100
9 hidden_layer_size = 5
10 activations = {}
11
12 for i in range(hidden_layer_size):
13     if i != 0:
14         x = activations[i-1]
15
16     w = np.random.randn(node_num, node_num) * 1
17
18     z = np.dot(x, w)
19     a = sigmoid(z)
20     activations[i] = a
21
22 for i, a in activations.items():
23     plt.subplot(1, len(activations), i+1)
24     plt.title(str(i+1) + "-layer")
25     plt.hist(a.flatten(), 30, range=(0,1))
26 plt.show()
27
28
```

重みの標準偏差を0.01にする。

```
#w = np.random.randn(node_num, node_num) * 1
w = np.random.randn(node_num, node_num) * 0.01
```



2 Section2_学習率最適化手法

学習率=0.1

```
1 import numpy as np
2
3 def numerical_gradient(f, x):
4     h = 1e-4
5     grad = np.zeros_like(x)
6
7     for idx in range(x.size):
8         tmp_val = x[idx]
9         x[idx] = tmp_val + h
10        fxh1 = f(x)
11
12        x[idx] = tmp_val - h
13        fxh2 = f(x)
14
15        grad[idx] = (fxh1 - fxh2) / (2*h)
16        x[idx] = tmp_val
17
18    return grad
19
20 def gradient_descent(f, init_x, lr=0.01, step_num=100):
21     x = init_x
22
23     for i in range(step_num):
24         grad = numerical_gradient(f, x)
25         x -= lr * grad
26
27    return x
28
29 def function_2(x):
30     return (x[0]**2 + x[1]**2)
31
32 init_x = np.array([-3.0, 4.0])
33 out = gradient_descent(function_2, init_x=init_x, lr=0.1, step_num=100)
34 print(out)
35
```

解は (0, 0)

```
[-6.11110793e-10  8.14814391e-10]
```

学習率=10.0

```
[-2.58983747e+13 -1.29524862e+12]
```

学習率=1e-10

```
[-2.99999994  3.99999992]
```

モーメンタム、Adagrad

```
1 import numpy as np
2
3 class Momentum:
4     def __init__(self, lr=0.01, momentum=0.9):
5         self.lr = lr
6         self.momentum = momentum
7         self.v = None
8
9     def update(self, params, grads):
10        if self.v is None:
11            self.v = {}
12            for key, val in params.items():
13                self.v[key] = np.zeros_like(val)
14
15            for key in params.keys():
16                self.v[key] = self.momentum*self.v[key] - self.lr*grads[key]
17                params[key] += self.v[key]
18
19 class Adagrad:
20     def __init__(self, lr=0.01):
21         self.lr = lr
22         self.h = None
23
24     def update(self, params, grads):
25        if self.h is None:
26            self.h = {}
27            for key, val in params.items():
28                self.h[key] = np.zeros_like(val)
29
30        for key in params.keys():
31            self.h[key] += grads[key] * grads[key]
32            params[key] -= self.lr * grads[key] / (np.sqrt(self.h[key]) + 1e-7)
```

3 Section3_過学習

MNIST データセットの訓練データを本来の 60,000 個から 300 個だけにする。

```
1  import numpy as np
2  import sys, os
3  sys.path.append(os.pardir)
4  from dataset.mnist import load_mnist
5
6  (x_train, t_train), (x_test, t_test) = load_mnist(normalize= True)
7  x_train = x_train[:300]
8  t_train = t_train[:300]
9
10 network = MultiLayerNet(input_size=784, hidden_size_list=[100, 100, 100, 100, 100,
11                                                                100], output_size=10)
12 optimizer = SGD(lr=0.01)
13
14 max_epochs = 201
15 train_size = x_train.shape[0]
16 batch_size = 100
17
18 train_loss_list = []
19 train_acc_list = []
20 test_acc_list = []
21
22 iter_per_epoch = max(train_size / batch_size, 1)
23 epoch_cnt = 0
24
25 for i in range(1000000000):
26     batch_mask = np.random.choice(train_size, batch_size)
27     x_batch = x_train[batch_mask]
28     t_batch = t_train[batch_mask]
29
30     grads = network.gradient(x_batch, t_batch)
31     optimizer.update(x_batch, t_batch)
32
33     if i % iter_per_epoch == 0:
34         train_acc = network.accuracy(x_train, t_train)
35         test_acc = network.accuracy(x_test, t_test)
36         train_acc_list.append(train_acc)
37         test_acc_list.append(test_acc)
38
39         epoch_cnt += 1
40         if epoch_cnt >= max_epochs:
41             break
42
```

4 Section4_畳み込みニューラルネットワーク

1) Convolution レイヤ

```
1 import numpy as np
2 import sys, os
3 sys.path.append(os.pardir)
4 from common.util import im2col
5
6 x1 = np.random.rand(1, 3, 7, 7)
7 col1 = im2col(x1, 5, 5, stride=1, pad=0)
8 print(col1.shape)
9
10 x2 = np.random.rand(10, 3, 7, 7)
11 col2 = im2col(x2, 5, 5, stride=1, pad=0)
12 print(col2.shape)
13
14 class convolution:
15     def __init__(self, w, b, stride=1, pad=0):
16         self.w = w
17         self.b = b
18         self.stride = stride
19         self.pad = pad
20
21     def forward(self, x):
22         FN, C, FH, FW = self.w.shape
23         N, C, H, W = x.shape
24         out_h = int(1 + (H + 2*self.pad - FH) / self.stride)
25         out_w = int(1 + (W + 2*self.pad - FW) / self.stride)
26
27         col = im2col(x, FH, FW, self.stride, self.pad)
28         col_w = self.w.reshape(FN, -1).T
29         out = np.dot(col, col_w) + self.b
30
31         out = out.reshape(N, out_h, out_w, -1).transpose(0, 3, 1, 2)
32
33         return out
34
35
36
```

2) pooling レイヤ

```
1 import numpy as np
2 import sys, os
3 sys.path.append(os.pardir)
4 from common.util import im2col
5
6 class pooling:
7     def __init__(self, pool_h, pool_w, stride=1, pad=0):
8         self.pool_h = pool_h
9         self.pool_w = pool_w
10        self.stride = stride
11        self.pad = pad
12
13    def forward(self, x):
14        N, C, H, W = x.shape
15        out_h = int(1 + (H - self.pool_h) / self.stride)
16        out_w = int(1 + (W - self.pool_w) / self.stride)
17
18        col = im2col(x, self.pool_h, self.pool_w, self.stride, self.pad)
19        col = col.reshape(-1, self.pool_h*self.pool_w)
20
21        out = np.max(col, axis=1)
22
23        out = out.reshape(N, out_h, out_w, C).transpose(0, 3, 1, 2)
24
25        return out
26
27
```

5 Section5_最新の CNN

CNN の実装

```
1 import numpy as np
2 import sys, os
3 sys.path.append(os.pardir)
4 from common.util import im2col
5
6 class SimpleConvNet:
7     def __init__(self, input_dim=(1, 28, 28),
8                 conv_param={'filter_num':30, 'filter_size':5,
9                             'pad':0, 'stride':1},
10                 hidden_size=100, output_size=10, weight_init_std=0.01):
11         filter_num = conv_param['filter_num']
12         filter_size = conv_param['filter_size']
13         filter_pad = conv_param['filter_pad']
14         filter_stride = conv_param['filter_stride']
15         input_size = input_dim[1]
16         conv_output_size = (input_size - filter_size + 2*filter_pad) / filter_stride + 1
17         pool_output_size = int(filter_num * (conv_output_size/2)*(conv_output_size/2))
18
19         self.params = {}
20         self.params['W'] = weight_init_std * np.random.randn(filter_num, input_dim[0],
21                                                                filter_size, filter_size)
22         self.params['b1'] = np.zeros(filter_num)
23         self.params['w2'] = weight_init_std * np.random.randn(pool_output_size,
24                                                                hidden_size)
25         self.params['b2'] = np.zeros(hidden_size)
26         self.params['w3'] = weight_init_std * np.random.randn(hidden_size, output_size)
27         self.params['b3'] = np.zeros(output_size)
28
29         self.layers = OrderedDict()
30         self.layers['Conv1'] = Convolution(self.params['w1'],
31                                           self.params['b1'],
32                                           conv_param['stride'],
33                                           conv_param['pad'])
34         self.layers['Relu1'] = Relu()
35         self.layers['Pool1'] = Pooling(pool_h=2, pool_w=2, stride=2)
36         self.layers['Affine1'] = Affine(self.params['w2'], self.params['b2'])
37         self.layers['Relu2'] = Relu()
38         self.layers['Affine2'] = Affine(self.params['w3'], self.params['b3'])
39
40         self.last_layer = SoftmaxwithLoss()
41
42
```