simpleconvnet2.py

```
# coding: utf-8
import sys, os
sys.path.append(os.pardir)  # 부모 디렉터리의 파일을 가져올 수 있도록 설정
import pickle
import numpy as np
from collections import OrderedDict
from common.layers import *
from common.gradient import numerical_gradient


class SimpleConvNet:
    def __init__(self, input_dim=(1, 28, 28),
                 conv_param={'filter_num':30, 'filter_size':5, 'pad':0,
'stride':1},
                 hidden_size=100, output_size=10, weight_init_std=0.01):  #
변수명 수정
        filter_num = conv_param['filter_num']
        filter_size = conv_param['filter_size']
        filter_pad = conv_param['pad']
        filter_stride = conv_param['stride']
        input_size = input_dim[1]
        conv_output_size = (input_size - filter_size + 2*filter_pad) //
filter_stride + 1
        pool_output_size = int(filter_num * (conv_output_size/2) *
(conv_output_size/2))

        # 가중치 초기화
        self.params = {}
        self.params['W1'] = weight_init_std * \
                            np.random.randn(filter_num, input_dim[0],
filter_size, filter_size)
        self.params['b1'] = np.zeros(filter_num)
        self.params['W2'] = weight_init_std * \
                            np.random.randn(pool_output_size, hidden_size)
        self.params['b2'] = np.zeros(hidden_size)
        self.params['W3'] = weight_init_std * \
                            np.random.randn(hidden_size, output_size)
        self.params['b3'] = np.zeros(output_size)

        # 계층 생성
        self.layers = OrderedDict()
        self.layers['Conv1'] = Convolution(self.params['W1'],
self.params['b1'],
                                           conv_param['stride'],
conv_param['pad'])
        self.layers['BatchNorm1'] = BatchNormalization(filter_num)
        self.layers['Relu1'] = Relu()
```

```python
        self.layers['Pool1'] = Pooling(pool_h=2, pool_w=2, stride=2)
        self.layers['Affine1'] = Affine(self.params['W2'], self.params['b2'])
        self.layers['BatchNorm2'] = BatchNormalization(hidden_size)
        self.layers['Relu2'] = Relu()
        self.layers['Dropout1'] = Dropout(dropout_ratio=0.5)
        self.layers['Affine2'] = Affine(self.params['W3'], self.params['b3'])

        self.last_layer = SoftmaxWithLoss()

        # Batch Normalization 파라미터 초기화
        self.gamma = {}
        self.beta = {}
        self.gamma['gamma1'] = np.ones(filter_num)
        self.beta['beta1'] = np.zeros(filter_num)
        self.gamma['gamma2'] = np.ones(hidden_size)
        self.beta['beta2'] = np.zeros(hidden_size)

        # 각 Batch Normalization 레이어에 파라미터 설정
        self.layers['BatchNorm1'].gamma = self.gamma['gamma1']
        self.layers['BatchNorm1'].beta = self.beta['beta1']
        self.layers['BatchNorm2'].gamma = self.gamma['gamma2']
        self.layers['BatchNorm2'].beta = self.beta['beta2']


    def predict(self, x):
        for layer in self.layers.values():
            x = layer.forward(x)

        return x

    def loss(self, x, t):
        y = self.predict(x)
        return self.last_layer.forward(y, t)

    def accuracy(self, x, t, batch_size=100):
        if t.ndim != 1 : t = np.argmax(t, axis=1)

        acc = 0.0

        for i in range(int(x.shape[0] / batch_size)):
            tx = x[i*batch_size:(i+1)*batch_size]
            tt = t[i*batch_size:(i+1)*batch_size]
            y = self.predict(tx)
            y = np.argmax(y, axis=1)
            acc += np.sum(y == tt)

        return acc / x.shape[0]

    def numerical_gradient(self, x, t):
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        loss_w = lambda w: self.loss(x, t)

        grads = {}
        for idx in (1, 2, 3):
            grads['W' + str(idx)] = numerical_gradient(loss_w, self.params['W'
+ str(idx)])
            grads['b' + str(idx)] = numerical_gradient(loss_w, self.params['b'
+ str(idx)])

        return grads

    def gradient(self, x, t):
        # forward
        self.loss(x, t)

        # backward
        dout = 1
        dout = self.last_layer.backward(dout)

        layers = list(self.layers.values())
        layers.reverse()
        for layer in layers:
            dout = layer.backward(dout)

        # 결과 저장
        grads = {}
        grads['W1'], grads['b1'] = self.layers['Conv1'].dW,
self.layers['Conv1'].db
        grads['W2'], grads['b2'] = self.layers['Affine1'].dW,
self.layers['Affine1'].db
        grads['W3'], grads['b3'] = self.layers['Affine2'].dW,
self.layers['Affine2'].db

        # Batch Normalization에 대한 gradient 추가
        grads['gamma1'] = self.layers['BatchNorm1'].dgamma
        grads['beta1'] = self.layers['BatchNorm1'].dbeta
        grads['gamma2'] = self.layers['BatchNorm2'].dgamma
        grads['beta2'] = self.layers['BatchNorm2'].dbeta

        return grads

    def save_params(self, file_name="params.pkl"):
        params = {}
        for key, val in self.params.items():
            params[key] = val
        with open(file_name, 'wb') as f:
            pickle.dump(params, f)
```

```
    def load_params(self, file_name="params.pkl"):
        with open(file_name, 'rb') as f:
            params = pickle.load(f)
        for key, val in params.items():
            self.params[key] = val

        for i, key in enumerate(['Conv1', 'Affine1', 'Affine2']):
            self.layers[key].W = self.params['W' + str(i+1)]
            self.layers[key].b = self.params['b' + str(i+1)]

        # Batch Normalization 파라미터 설정
        self.layers['BatchNorm1'].gamma = self.gamma['gamma1']
        self.layers['BatchNorm1'].beta = self.beta['beta1']
        self.layers['BatchNorm2'].gamma = self.gamma['gamma2']
        self.layers['BatchNorm2'].beta = self.beta['beta2']
    def __init__(self, input_dim=(1, 28, 28),
                 conv_param={'filter_num':30, 'filter_size':5, 'pad':0,
'stride':1},
                 hidden_size=100, output_size=10, weight_init_std=0.01):  #
변수명 수정
        filter_num = conv_param['filter_num']
        filter_size = conv_param['filter_size']
        filter_pad = conv_param['pad']
        filter_stride = conv_param['stride']
        input_size = input_dim[1]
        conv_output_size = (input_size - filter_size + 2*filter_pad) /
filter_stride + 1
        pool_output_size = int(filter_num * (conv_output_size/2) *
(conv_output_size/2))

        # 가중치 초기화
        self.params = {}
        self.params['W1'] = weight_init_std * \
                            np.random.randn(filter_num, input_dim[0],
filter_size, filter_size)
        self.params['b1'] = np.zeros(filter_num)
        self.params['W2'] = weight_init_std * \
                            np.random.randn(pool_output_size, hidden_size)
        self.params['b2'] = np.zeros(hidden_size)
        self.params['W3'] = weight_init_std * \
                            np.random.randn(hidden_size, output_size)
        self.params['b3'] = np.zeros(output_size)

        # 계층 생성
        self.layers = OrderedDict()
        self.layers['Conv1'] = Convolution(self.params['W1'],
self.params['b1'],
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                                           conv_param['stride'],
conv_param['pad'])
        self.layers['Relu1'] = Relu()
        self.layers['Pool1'] = Pooling(pool_h=2, pool_w=2, stride=2)
        self.layers['Affine1'] = Affine(self.params['W2'], self.params['b2'])
        self.layers['Relu2'] = Relu()
        self.layers['Dropout1'] = Dropout(dropout_ratio=0.5)
        self.layers['Affine2'] = Affine(self.params['W3'], self.params['b3'])

        self.last_layer = SoftmaxWithLoss()


    def predict(self, x):
        for layer in self.layers.values():
            x = layer.forward(x)

        return x

    def loss(self, x, t):
        y = self.predict(x)
        return self.last_layer.forward(y, t)

    def accuracy(self, x, t, batch_size=100):
        if t.ndim != 1 : t = np.argmax(t, axis=1)

        acc = 0.0

        for i in range(int(x.shape[0] / batch_size)):
            tx = x[i*batch_size:(i+1)*batch_size]
            tt = t[i*batch_size:(i+1)*batch_size]
            y = self.predict(tx)
            y = np.argmax(y, axis=1)
            acc += np.sum(y == tt)

        return acc / x.shape[0]

    def numerical_gradient(self, x, t):
        loss_w = lambda w: self.loss(x, t)

        grads = {}
        for idx in (1, 2, 3):
            grads['W' + str(idx)] = numerical_gradient(loss_w, self.params['W'
+ str(idx)])
            grads['b' + str(idx)] = numerical_gradient(loss_w, self.params['b'
+ str(idx)])

        return grads

    def gradient(self, x, t):
```

```
        # forward
        self.loss(x, t)

        # backward
        dout = 1
        dout = self.last_layer.backward(dout)

        layers = list(self.layers.values())
        layers.reverse()
        for layer in layers:
            dout = layer.backward(dout)

        # 결과 저장
        grads = {}
        grads['W1'], grads['b1'] = self.layers['Conv1'].dW,
self.layers['Conv1'].db
        grads['W2'], grads['b2'] = self.layers['Affine1'].dW,
self.layers['Affine1'].db
        grads['W3'], grads['b3'] = self.layers['Affine2'].dW,
self.layers['Affine2'].db

        return grads

    def save_params(self, file_name="params.pkl"):
        params = {}
        for key, val in self.params.items():
            params[key] = val
        with open(file_name, 'wb') as f:
            pickle.dump(params, f)

    def load_params(self, file_name="params.pkl"):
        with open(file_name, 'rb') as f:
            params = pickle.load(f)
        for key, val in params.items():
            self.params[key] = val

        for i, key in enumerate(['Conv1', 'Affine1', 'Affine2']):
            self.layers[key].W = self.params['W' + str(i+1)]
            self.layers[key].b = self.params['b' + str(i+1)]
```

train_cnn.py

```
# coding: utf-8
import sys, os
sys.path.append(os.pardir)  # 부모 디렉터리의 파일을 가져올 수 있도록 설정
```

```python
import numpy as np
import matplotlib.pyplot as plt
from dataset.fasion_mnist import load_mnist
from simpleconvnet2 import SimpleConvNet
from common.trainer import Trainer

# 데이터 읽기
(x_train, t_train), (x_test, t_test) = load_mnist(flatten=False)

# 시간이 오래 걸릴 경우 데이터를 줄인다.
x_train, t_train = x_train[:20000], t_train[:20000]
x_test, t_test = x_test[:4000], t_test[:4000]

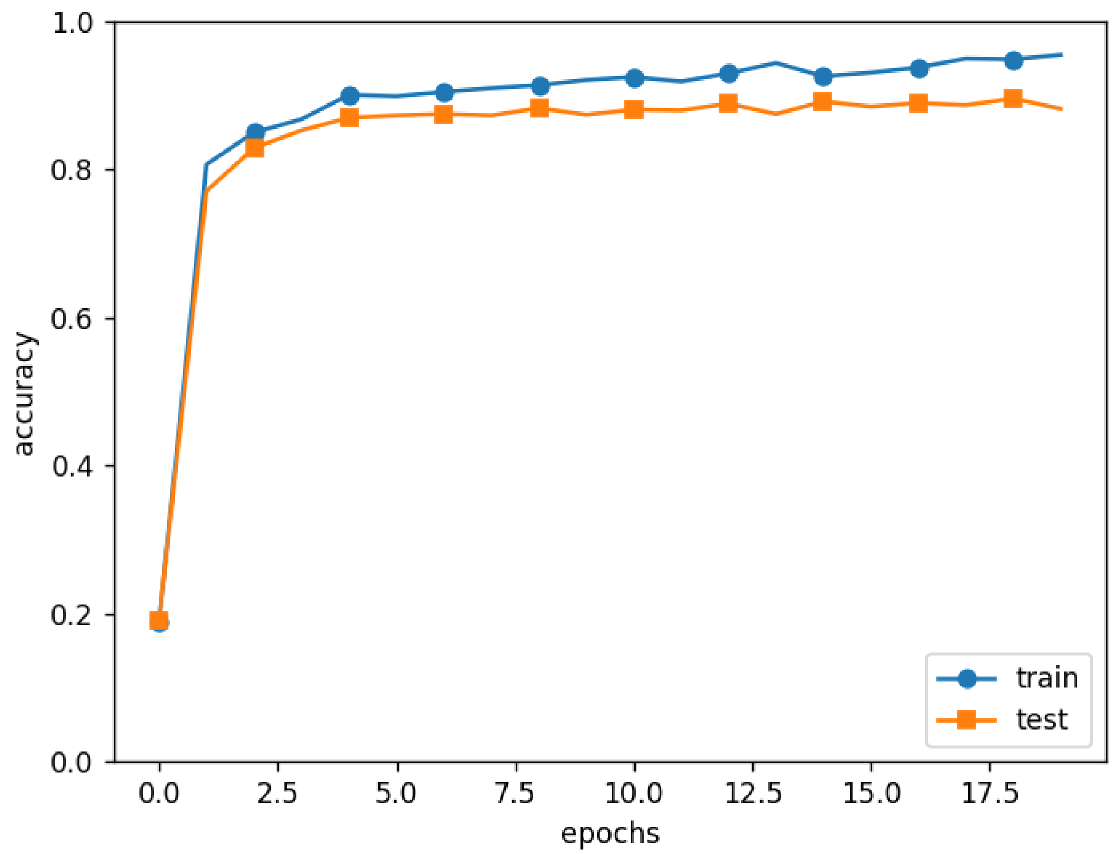
max_epochs = 20

network = SimpleConvNet(input_dim=(1,28,28),
                        conv_param = {'filter_num': 64, 'filter_size': 5,
'pad': 0, 'stride': 1},
                        hidden_size=512, output_size=10, weight_init_std=0.01)

trainer = Trainer(network, x_train, t_train, x_test, t_test,
                  epochs=max_epochs, mini_batch_size=100,
                  optimizer='Adam', optimizer_param={'lr': 0.001},
                  evaluate_sample_num_per_epoch=1000)
trainer.train()

# 매개변수 보존
network.save_params("params.pkl")
print("Saved Network Parameters!")

# 그래프 그리기
markers = {'train': 'o', 'test': 's'}
x = np.arange(max_epochs)
plt.plot(x, trainer.train_acc_list, marker='o', label='train', markevery=2)
plt.plot(x, trainer.test_acc_list, marker='s', label='test', markevery=2)
plt.xlabel("epochs")
plt.ylabel("accuracy")
plt.ylim(0, 1.0)
plt.legend(loc='lower right')
plt.show()
```



터미널 로그

```
train loss:0.30602533008461524
train loss:0.1712600997502639
=== epoch:16, train acc:0.931, test acc:0.885 ===
train loss:0.08476040627640194
train loss:0.1250027929148154
train loss:0.18457773447367667
train loss:0.18345250394402146
train loss:0.16031079869083062
train loss:0.18400510962112043
train loss:0.22157897368144283
train loss:0.15645936315662792
train loss:0.1146363423743681
train loss:0.1645773362269976
train loss:0.21738852287201596
train loss:0.3225849508101129
train loss:0.13184791839743165
train loss:0.19092666098441705
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train loss:0.14589439581205782
train loss:0.2667051796895035
train loss:0.163526378601826
train loss:0.1751872027988046
train loss:0.21186184480109962
train loss:0.14668707950235113
train loss:0.09648436442363711
train loss:0.13151527179213562
train loss:0.1742631044302337
train loss:0.21545254029467306
train loss:0.2374784602251524
train loss:0.146019862271164
train loss:0.1701703794837011
train loss:0.16731818792648442
train loss:0.12683735954998293
train loss:0.2612902334219262
train loss:0.20397952330711008
train loss:0.2012930824856069
train loss:0.1425609859501112
train loss:0.13671137954794177
train loss:0.1715601569429744
train loss:0.1617351936344051
train loss:0.15073648239784673
train loss:0.1299277693347017
train loss:0.23615820120926947
train loss:0.2684398199087685
train loss:0.1783753579033519
train loss:0.1934622485270115
train loss:0.16409529419750107
train loss:0.1865576118740954
train loss:0.2782115465979958
train loss:0.09878710850453999
train loss:0.1782622614581687
train loss:0.14473285608049385
train loss:0.0989675302339554
train loss:0.116083496099523
train loss:0.21858546708213364
train loss:0.2344939415843013
train loss:0.1863690734448328
train loss:0.25098434342375997
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train loss:0.13747440703832742
train loss:0.17638570216797184
train loss:0.25852658362312636
train loss:0.1610940604561436
train loss:0.23454237626437602
train loss:0.2236866779429041
train loss:0.1524815503704649
train loss:0.16482244286597494
train loss:0.20551507915258577
train loss:0.16550296065620437
train loss:0.10006922637342985
train loss:0.12370839000754827
train loss:0.1384594807943883
train loss:0.13142402763205918
train loss:0.18778615845715455
train loss:0.1606817295566969
train loss:0.16367000355695255
train loss:0.09975882964468903
train loss:0.30037939394213375
train loss:0.14317801168099012
train loss:0.17575476126575432
train loss:0.11404861062649146
train loss:0.1606289573778532
train loss:0.14333313970223074
train loss:0.13276185104171614
train loss:0.18183385256166607
train loss:0.1293400440940769
train loss:0.24396695288810136
train loss:0.1529225348696656
train loss:0.21967990311920196
train loss:0.1992262517171438
train loss:0.143060315517026
train loss:0.15280188675708584
train loss:0.10287926584456407
train loss:0.24140913373988734
train loss:0.1870500295849155
train loss:0.0841730150688306
train loss:0.2022460616434243
train loss:0.11642217537443658
train loss:0.11937682023479355
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train loss:0.0673098817462908
train loss:0.12525611533242842
train loss:0.1109087947632086
train loss:0.24065122410324358
train loss:0.1546108521513861
train loss:0.15580720103607637
train loss:0.10583387899424053
train loss:0.14714132984615547
train loss:0.12399936598343311
train loss:0.10839448697463862
train loss:0.11036297769155919
train loss:0.11873157284979147
train loss:0.24351233988060753
train loss:0.12324253788941554
train loss:0.1497984778714039
train loss:0.1701123586949941
train loss:0.18416963189618535
train loss:0.1770264912893061
train loss:0.161243835146896
train loss:0.14386682232890777
train loss:0.09260391826776017
train loss:0.13632604554608474
train loss:0.10196360568597129
train loss:0.2195634995982283
train loss:0.21596630654595156
train loss:0.16214928441889778
train loss:0.16673085142267838
train loss:0.12131580934124088
train loss:0.08885168131146502
train loss:0.13503990248524272
train loss:0.1347158680695604
train loss:0.14137909822665595
train loss:0.2664375723284402
train loss:0.229714887790168
train loss:0.16155782431429677
train loss:0.10186815044400252
train loss:0.18981780714989369
train loss:0.1382911447209744
train loss:0.17511264311724253
train loss:0.14881044861610612
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train loss:0.1811526434493346
train loss:0.2100253920240505
train loss:0.2143083194327534
train loss:0.13006816594763396
train loss:0.14294911258694637
train loss:0.07134111836352687
train loss:0.13697322585915156
train loss:0.2203695052647434
train loss:0.15480252384652457
train loss:0.10468303096434087
train loss:0.16414718106190598
train loss:0.0894430683300885
train loss:0.18306139019189197
train loss:0.13229165909007792
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train loss:0.19296691956391385
train loss:0.24066995230421884
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train loss:0.11690092826541573
train loss:0.18172526443004983
train loss:0.10882525364874493
train loss:0.23139564519695213
train loss:0.22328891299041614
train loss:0.1893277475188539
train loss:0.1524454300509869
train loss:0.19988370138302267
train loss:0.20520303859518993
train loss:0.13817470698213424
train loss:0.17320165025188705
train loss:0.1520947824437025
train loss:0.14427925910937034
train loss:0.16268559055279583
train loss:0.3040211505399943
train loss:0.24440325380877714
train loss:0.12471827575601706
train loss:0.13690620045140206
train loss:0.1327958999022491
train loss:0.10657075950882162
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train loss:0.10785093997356826
train loss:0.2769274647919164
train loss:0.12380276210205735
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train loss:0.12605861679312624
train loss:0.12815430397064417
train loss:0.20989325184680896
train loss:0.19046764337318425
train loss:0.1913079898403104
train loss:0.18640170923340268
train loss:0.16056958753154685
train loss:0.15810288316031967
train loss:0.28522008498907775
train loss:0.09979076835669433
train loss:0.12200753311679755
train loss:0.08677765828020227
train loss:0.1933852620919164
train loss:0.16004184518324288
train loss:0.16794288916248898
train loss:0.18346057240954525
train loss:0.07059920518230177
train loss:0.10168876300116787
train loss:0.14442539825107326
train loss:0.1730887625313941
train loss:0.22560781149882708
train loss:0.10878260639815726
=== epoch:17, train acc:0.938, test acc:0.89 ===
train loss:0.15576537063126655
train loss:0.112700874812491
train loss:0.15796207845091106
train loss:0.14642130950772914
train loss:0.13304065279163418
train loss:0.16415033091258946
train loss:0.1568465161756291
train loss:0.2396583161050314
train loss:0.15551892729526381
train loss:0.12889076500010982
train loss:0.11279727655362036
train loss:0.13780498979336453
train loss:0.14159166244317611
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train loss:0.09064580717682334
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train loss:0.13883435929084256
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train loss:0.14294152670178562
train loss:0.1718773949157273
train loss:0.1901771615463873
train loss:0.16857225709675194
train loss:0.11725074178530023
train loss:0.14490400781295137
train loss:0.11426783256298682
train loss:0.18143021893067776
train loss:0.10959371337827788
train loss:0.06803927187070519
train loss:0.1579769833791106
train loss:0.11865465844829842
train loss:0.1765127003535238
train loss:0.1289490218080193
train loss:0.18512381048644472
train loss:0.18762694097069435
train loss:0.09622050272659971
train loss:0.21711292680184105
train loss:0.2327176723186666
train loss:0.14897767816533516
train loss:0.16173525526220783
train loss:0.09233146306019403
train loss:0.2148309122159491
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train loss:0.2642190688321138
train loss:0.11238163242857672
train loss:0.14422232023563594
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train loss:0.11038516452347662
train loss:0.12007369918235192
train loss:0.15266317280007122
train loss:0.14727865690967565
train loss:0.14889658879011247
train loss:0.13548070924923317
train loss:0.11283932036735521
train loss:0.2423078370152971
train loss:0.1413817431118468
train loss:0.18254959226894918
train loss:0.1447103230829425
train loss:0.1438994651563158
train loss:0.11799715932192649
train loss:0.16687674200757768
train loss:0.2322211508703632
train loss:0.1401487322336045
train loss:0.10338992739092667
train loss:0.14380481911108736
train loss:0.1489040381052328
train loss:0.1798594398257446
train loss:0.09473894726315814
train loss:0.12638590226310323
train loss:0.1211346318811584
train loss:0.23358174108839033
train loss:0.1338068739180509
train loss:0.045063291699581856
train loss:0.06393947449782628
train loss:0.1236916354330152
train loss:0.1171111741758381
train loss:0.2125344310818887
train loss:0.2299394840995301
train loss:0.11169460607487917
train loss:0.13006996668735854
train loss:0.21050060766282705
train loss:0.15137359827772415
train loss:0.17305532076000837
train loss:0.1026614392945495
train loss:0.16695815727779315
train loss:0.14137766049062564
train loss:0.2949471295738201
```

```
train loss:0.1231000746728686
train loss:0.09806115874903948
train loss:0.12060477742399352
train loss:0.1676724102131352
train loss:0.18296130891604412
train loss:0.10526155114971032
train loss:0.13309202331683356
train loss:0.20491733677352858
train loss:0.16859966628415488
train loss:0.1648292227077391
train loss:0.21672182752766145
train loss:0.17790226842878862
train loss:0.1853202316890673
train loss:0.11399759136700517
train loss:0.169743527637277
train loss:0.1516655822103821
train loss:0.14731820730398956
train loss:0.20164239823658733
train loss:0.09534339680393494
train loss:0.09236349259708977
train loss:0.21274639037132734
train loss:0.2126301770201508
train loss:0.14691932562522506
train loss:0.14615395822254024
train loss:0.23431705231515335
train loss:0.1312231050845417
train loss:0.1189844846262136
train loss:0.11921411383926732
train loss:0.15491568651818513
train loss:0.10080267063269473
train loss:0.20297250218170793
train loss:0.1841018873171771
train loss:0.129507065640939
train loss:0.22560495327016158
train loss:0.15312768095679608
train loss:0.1261339056836192
train loss:0.14309415398050196
train loss:0.09879974926596148
train loss:0.11640865938069536
train loss:0.1820343434845716
```

```
train loss:0.1444694710558735
train loss:0.07341190408661667
train loss:0.17413418209683992
train loss:0.13799395568341422
train loss:0.2261645850074664
train loss:0.1758849012879381
train loss:0.15936662464191337
train loss:0.2519726647760806
train loss:0.16512793884938315
train loss:0.1527193789995752
train loss:0.15010324735016917
train loss:0.10349305713309878
train loss:0.16643097630924125
train loss:0.22822693492616028
train loss:0.1442096933152883
train loss:0.11264757308687105
train loss:0.13661497037851655
train loss:0.12954759231510685
train loss:0.20220235051485755
train loss:0.13044194668148887
train loss:0.15285473716878759
train loss:0.11029161191996474
train loss:0.12580878710524737
train loss:0.146561305093764
train loss:0.0909468750592728
train loss:0.1992978239428166
train loss:0.15869550604160487
train loss:0.10071460861202225
train loss:0.13683653073520005
train loss:0.15455097577470533
train loss:0.17121092826357326
train loss:0.17919549811203556
train loss:0.17046373262375847
train loss:0.12969923987069726
train loss:0.1265749852838109
train loss:0.16154209392953917
train loss:0.1769585907061903
train loss:0.25728665868107764
train loss:0.1910597870976538
train loss:0.2032095015029446
```

```
train loss:0.18180043332358828
train loss:0.10096729742012926
train loss:0.24660285353683456
train loss:0.160964077676459
train loss:0.07518239709220514
train loss:0.13840044937955745
train loss:0.1342618747028166
train loss:0.10027675033953427
train loss:0.10118930419742751
train loss:0.10565990963727004
train loss:0.14158620690859372
train loss:0.09320156202212279
train loss:0.14735524048502455
train loss:0.23104606836654987
train loss:0.13539456794010715
train loss:0.15675108286784445
train loss:0.08658266460079415
train loss:0.20836103878683832
train loss:0.17792020978582365
train loss:0.1299747607485624
train loss:0.10597685126295567
train loss:0.20619418059758365
train loss:0.13776836315024782
train loss:0.15727967191020376
train loss:0.13917508168046072
train loss:0.11931719256456244
train loss:0.17318063158553543
=== epoch:18, train acc:0.95, test acc:0.887 ===
train loss:0.17537019955323438
train loss:0.16180189665724412
train loss:0.09387582020934053
train loss:0.11801039890474047
train loss:0.20800822347660397
train loss:0.12221102185938568
train loss:0.11399024653614165
train loss:0.19437109583919499
train loss:0.12054501044383285
train loss:0.08827980978639101
train loss:0.17268603976938646
train loss:0.08491148338747906
```

```
train loss:0.1298211593305578
train loss:0.16852091179769077
train loss:0.14740841860795836
train loss:0.12541038339525631
train loss:0.1457088062562953
train loss:0.16124965706238512
train loss:0.16861654305249252
train loss:0.17156180454457978
train loss:0.24587571336137798
train loss:0.28360372152827346
train loss:0.060644237624961725
train loss:0.26093527778385095
train loss:0.14505509414482512
train loss:0.09603229790299193
train loss:0.13808311488154504
train loss:0.13661559341376256
train loss:0.26030698145324155
train loss:0.1883696085717065
train loss:0.16294717550986187
train loss:0.08827422523064721
train loss:0.11525132365351237
train loss:0.07226508524831378
train loss:0.13375843719708824
train loss:0.18484392228036717
train loss:0.1554085118490713
train loss:0.11193635325495442
train loss:0.1187927524501276
train loss:0.13428024966819546
train loss:0.14277903805434244
train loss:0.19205946413534125
train loss:0.20727058826670308
train loss:0.09503050903457835
train loss:0.1608625061479559
train loss:0.18152918818188646
train loss:0.19654210882852916
train loss:0.12678693449662007
train loss:0.0512702073133336
train loss:0.15759942519641815
train loss:0.15067196473432082
train loss:0.14589851962940645
```

```
train loss:0.07380126371943356
train loss:0.09038089188331512
train loss:0.11531189661573686
train loss:0.2018969965354902З
train loss:0.09693224739523744
train loss:0.1854228618598264
train loss:0.19992108670321268
train loss:0.1874721675754677
train loss:0.11579672083592235
train loss:0.18661130657296887
train loss:0.10332797449257733
train loss:0.12223304218319378
train loss:0.11315218005381958
train loss:0.1455945319746632
train loss:0.22352103928255004
train loss:0.14605482144664383
train loss:0.24634510681095154
train loss:0.10307940808310771
train loss:0.21799053804890536
train loss:0.169866132406386
train loss:0.14895288001019477
train loss:0.12793338541489946
train loss:0.10503965545168831
train loss:0.11429621591301867
train loss:0.16471441889142163
train loss:0.14174477591176435
train loss:0.14107695168700762
train loss:0.2200597140968774
train loss:0.11775914731738572
train loss:0.07558616234827503
train loss:0.17005832703047413
train loss:0.06190734108763527
train loss:0.10770807399252784
train loss:0.13517896399816956
train loss:0.12750721716671318
train loss:0.10310104983647556
train loss:0.20173089616296236
train loss:0.18522096653439263
train loss:0.16582223381326358
train loss:0.09923680337992799
```

```
train loss:0.09127459281220855
train loss:0.10558504094652893
train loss:0.11694208871666355
train loss:0.18923468244262012
train loss:0.13353628179259888
train loss:0.15493744738727458
train loss:0.07458053734808433
train loss:0.20157879201573933
train loss:0.2779659980591634
train loss:0.1617629768880063
train loss:0.15928979046171865
train loss:0.22007105727590814
train loss:0.13243421244245127
train loss:0.09534057360209233
train loss:0.07735807746982608
train loss:0.1886611773221618
train loss:0.11780571372418548
train loss:0.15229069107910292
train loss:0.1369278288766704
train loss:0.17865822316483743
train loss:0.09529139852658927
train loss:0.1428596651803221
train loss:0.11642384176691206
train loss:0.15487443326492845
train loss:0.18656572702484553
train loss:0.20304459799202587
train loss:0.17383645804786846
train loss:0.15729001280618238
train loss:0.14372222393403428
train loss:0.11193018265786987
train loss:0.23817290127385213
train loss:0.12498761870687558
train loss:0.15257376289914557
train loss:0.10891763506239113
train loss:0.08624538454506771
train loss:0.16979141931081604
train loss:0.16396988618423097
train loss:0.14480866325579256
train loss:0.15694387153284317
train loss:0.11899252678627543
```

```
train loss:0.13749453302567516
train loss:0.1127903570021272
train loss:0.08688800324433844
train loss:0.196724033259469
train loss:0.12046658073087632
train loss:0.12713130134754785
train loss:0.10476246272326765
train loss:0.15817101516757343
train loss:0.1755579155531416
train loss:0.12604978785819448
train loss:0.07263528113609269
train loss:0.09020667276050508
train loss:0.1454029960133776
train loss:0.1334909814909542
train loss:0.16311309556026526
train loss:0.0844473530277462
train loss:0.07409648440031996
train loss:0.20965368410025725
train loss:0.1929361974260508
train loss:0.15695182166026295
train loss:0.10278503077072129
train loss:0.08022863736538344
train loss:0.12928287006066727
train loss:0.14056601483822567
train loss:0.07126057068309116
train loss:0.10903079715637436
train loss:0.15789626797071216
train loss:0.1732689861360636
train loss:0.20932080737015712
train loss:0.18641150635072562
train loss:0.14888265444985968
train loss:0.24843783935400185
train loss:0.12136552901512827
train loss:0.12185212467670414
train loss:0.1070463951807533
train loss:0.12214927080841313
train loss:0.18595441131189122
train loss:0.20891706979619026
train loss:0.21274658356202183
train loss:0.0767070526405129
```

```
train loss:0.13229147804438668
train loss:0.19323149546466145
train loss:0.1364597093596036
train loss:0.19985803473486133
train loss:0.07800169279897522
train loss:0.2073364300813019
train loss:0.14626207159633653
train loss:0.12112434685202553
train loss:0.12626984667095015
train loss:0.23133036076275246
train loss:0.15536205084830956
train loss:0.17048430716374244
train loss:0.16302869844729595
train loss:0.17681283087596728
train loss:0.17420406727319154
train loss:0.07914184267133505
train loss:0.15746949090874135
train loss:0.08945067474445483
train loss:0.12881523426652086
train loss:0.13103961223934057
train loss:0.12979080978276594
train loss:0.078134098610036
train loss:0.07457001378870926
train loss:0.08746116633419548
train loss:0.1795215207346472
train loss:0.258472464906153
train loss:0.11611929213506608
train loss:0.19513821602508208
=== epoch:19, train acc:0.949, test acc:0.896 ===
train loss:0.11143859216957497
train loss:0.09395205188351055
train loss:0.179007549927113
train loss:0.10412817191549212
train loss:0.21178870284766227
train loss:0.1310968872286495
train loss:0.14001404634552755
train loss:0.0861928189013716
train loss:0.21381767827956927
train loss:0.13547467538214955
train loss:0.16361294648007224
```

```
train loss:0.18898301917795846
train loss:0.14952440885722929
train loss:0.07478521960202976
train loss:0.1516657031042816
train loss:0.11991095245117057
train loss:0.08963155512645594
train loss:0.22812575736604151
train loss:0.14291580767530734
train loss:0.1805559195366368
train loss:0.16272801450102278
train loss:0.07335313934900968
train loss:0.1339180001556932
train loss:0.08935133572271178
train loss:0.12845783393006482
train loss:0.18044687417609784
train loss:0.11072981506675243
train loss:0.15098912153837651
train loss:0.12072032622867361
train loss:0.14725682121717468
train loss:0.2026347411972892
train loss:0.10746157481204646
train loss:0.06080219668174983
train loss:0.16696483481944632
train loss:0.13072148666503225
train loss:0.08819423841328858
train loss:0.12761183665914597
train loss:0.11075728321910193
train loss:0.1354956223052252
train loss:0.15133350548071703
train loss:0.20022367827641346
train loss:0.10702575755159627
train loss:0.081066662802118
train loss:0.20755411128584472
train loss:0.13072033971182162
train loss:0.11818887882567897
train loss:0.09865761164816819
train loss:0.1466237395758451
train loss:0.14352198233360614
train loss:0.15893646507736386
train loss:0.09892009620187507
```

```
train loss:0.16957543702579084
train loss:0.14780909676105977
train loss:0.0885120218895344
train loss:0.15147439794035086
train loss:0.1721262099053051
train loss:0.16679318467539203
train loss:0.19918158842838476
train loss:0.07022311924381826
train loss:0.061856775362436306
train loss:0.10287431225665378
train loss:0.19557422006606803
train loss:0.12597375033965652
train loss:0.14071228833838623
train loss:0.12209099617193382
train loss:0.11045337887501731
train loss:0.1341458635124119
train loss:0.10221299743594167
train loss:0.12102516087166823
train loss:0.17033223257155108
train loss:0.10058569770742802
train loss:0.08980033355320577
train loss:0.20441806451817918
train loss:0.14693398517679002
train loss:0.08992241939499122
train loss:0.1411427550659983
train loss:0.11190777652415487
train loss:0.16031686613427062
train loss:0.08188850775853834
train loss:0.10899631007123768
train loss:0.1468963701865738
train loss:0.15884900797082144
train loss:0.24616215329196175
train loss:0.20621972031813363
train loss:0.09372198523624135
train loss:0.14415067201212875
train loss:0.13770313571748333
train loss:0.15202981207443894
train loss:0.16367095341312013
train loss:0.1768137622195043
train loss:0.2057124379628101
```

```
train loss:0.1036861005206901
train loss:0.16243915532397613
train loss:0.11092591441494636
train loss:0.18977045100342907
train loss:0.09351123672786259
train loss:0.09864164652531197
train loss:0.10486560398589422
train loss:0.15370166934668972
train loss:0.08247051781016186
train loss:0.15621529361419556
train loss:0.1434287228382348
train loss:0.14163301227157826
train loss:0.17690139964327906
train loss:0.14430379222546605
train loss:0.13666767209806258
train loss:0.22474206028464613
train loss:0.12025091797504184
train loss:0.15235739290310632
train loss:0.23111501258869674
train loss:0.15919092881650568
train loss:0.10979741920002407
train loss:0.10618833350758848
train loss:0.11163541809576732
train loss:0.12037064701914382
train loss:0.11188171094489383
train loss:0.10937397614685036
train loss:0.08181686270926061
train loss:0.16818363372850167
train loss:0.09819031573887288
train loss:0.26009576765173864
train loss:0.10958169355784118
train loss:0.2039963109417855
train loss:0.15859234016578916
train loss:0.11299123927900459
train loss:0.18864299317693148
train loss:0.2354201811807639
train loss:0.044375026467761994
train loss:0.09340187446259138
train loss:0.1143795503201156
train loss:0.08046724064705843
```

```
train loss:0.07841688599130463
train loss:0.0890534105585898
train loss:0.10034538171846222
train loss:0.16133089019458496
train loss:0.17617667227454695
train loss:0.1111926202304052
train loss:0.13390845951021732
train loss:0.1646649325625429
train loss:0.1513747885370627
train loss:0.1446677933389967
train loss:0.14626912846361254
train loss:0.17851359934753971
train loss:0.13018895938503808
train loss:0.17945771160036095
train loss:0.1717124946191588
train loss:0.2249737432918529
train loss:0.14729537686433156
train loss:0.11262001528034409
train loss:0.1021992738458128
train loss:0.1359583623452396
train loss:0.14627390796927972
train loss:0.12196918289731555
train loss:0.10683076857556358
train loss:0.1443595394783013
train loss:0.15497453942139064
train loss:0.1659101658818875
train loss:0.09931371284867872
train loss:0.07497232329180509
train loss:0.09707142458568643
train loss:0.14680682827769728
train loss:0.10183397082182713
train loss:0.17212762587008726
train loss:0.19982346644410268
train loss:0.11682481241708748
train loss:0.11898157807976126
train loss:0.10088649669232316
train loss:0.11489029072571219
train loss:0.14388261838389224
train loss:0.07712257949844198
train loss:0.09877607770931923
```

```
train loss:0.13630607601410957
train loss:0.1138658303728431
train loss:0.12307106300438636
train loss:0.09306323080982531
train loss:0.17413615052986386
train loss:0.1313649793552279
train loss:0.1533473533698079
train loss:0.17306999664963063
train loss:0.2084770338365483
train loss:0.10039845036198035
train loss:0.15551054258728403
train loss:0.12482813470518106
train loss:0.15439317468093555
train loss:0.06609623607517637
train loss:0.11251555822299862
train loss:0.08155816817514762
train loss:0.23178180273566182
train loss:0.1788530375203279
train loss:0.1790073722385296
train loss:0.113585554676113
train loss:0.18988942007065682
train loss:0.13319197562375945
train loss:0.11304175601796232
train loss:0.09308483999935101
train loss:0.14994189481506284
train loss:0.09784439603565245
train loss:0.16875014980537087
train loss:0.16228642594025833
train loss:0.1114560622078618
=== epoch:20, train acc:0.955, test acc:0.882 ===
train loss:0.13054334521778402
train loss:0.08650651438246826
train loss:0.16365974724417065
train loss:0.1017148036971431
train loss:0.08586808720059226
train loss:0.1851266547645935
train loss:0.15316504472773093
train loss:0.1393058309313634
train loss:0.13986146989670498
train loss:0.09226279817385566
```

```
train loss:0.12191040952769903
train loss:0.1382717065168234
train loss:0.14271862215762882
train loss:0.07043166501024568
train loss:0.1175894096013115
train loss:0.12469569399017218
train loss:0.11446096391420452
train loss:0.2021121061695028
train loss:0.137196178340597
train loss:0.0406347834634601
train loss:0.07160884179858874
train loss:0.09465993377573763
train loss:0.18493212547042578
train loss:0.13678908502846843
train loss:0.10481061211489977
train loss:0.14304152497254546
train loss:0.23666448592726905
train loss:0.18990476620675092
train loss:0.10989222902987272
train loss:0.14885804233099567
train loss:0.19233221107486875
train loss:0.18770698522673304
train loss:0.09659328375281837
train loss:0.10550769315009177
train loss:0.12978774127085407
train loss:0.15296931648300283
train loss:0.15175202750842393
train loss:0.13185649229758298
train loss:0.06739182188394847
train loss:0.19462596053970857
train loss:0.0699863227782978
train loss:0.13467194420954962
train loss:0.121365152664253
train loss:0.05807312794720758
train loss:0.1076011930581285
train loss:0.1285967951871514
train loss:0.05996451330790269
train loss:0.2012468061331701
train loss:0.049194272211594246
train loss:0.11157730386646944
```

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train loss:0.06411511854657846
train loss:0.1115247597628505
train loss:0.12195354661749923
train loss:0.12229742491627256
train loss:0.14102369941891202
train loss:0.21847526415989577
train loss:0.1251381257141762
train loss:0.0925735896274367
train loss:0.07264991872117937
train loss:0.12568313234145256
train loss:0.11145946786275146
train loss:0.12403011198660098
train loss:0.1474340890138929
train loss:0.1177238905499523
train loss:0.1329505991075082
train loss:0.17548167054502536
train loss:0.17852903421985705
train loss:0.1578683928931949
train loss:0.09861935240989075
train loss:0.12465284194498139
train loss:0.07236078652802788
train loss:0.1296126563182788
train loss:0.11249520800099842
train loss:0.19664459552911637
train loss:0.13346619156116454
train loss:0.15950548839743636
train loss:0.09354414910869183
train loss:0.19705022246071524
train loss:0.06858440520752249
train loss:0.15354362032474028
train loss:0.15359877060365085
train loss:0.10741370580992067
train loss:0.10752455305611615
train loss:0.17560658789167957
train loss:0.09536055885869234
train loss:0.04438929931128448
train loss:0.17333501753922462
train loss:0.0627990095864866
train loss:0.12120355318439731
train loss:0.1562805382101806
```

```
train loss:0.11396195865139724
train loss:0.09474978426682747
train loss:0.12864252463132705
train loss:0.17516333329772193
train loss:0.17823492739452146
train loss:0.12288128100316259
train loss:0.17676072420685898
train loss:0.14734272951838176
train loss:0.11468785857268275
train loss:0.1276577921843237
train loss:0.09310695852257526
train loss:0.1606924163667078
train loss:0.0853253075838659
train loss:0.13560518372863514
train loss:0.14638837946218763
train loss:0.18487850146649604
train loss:0.11561384303711675
train loss:0.1285777732045747
train loss:0.14597231070513458
train loss:0.19419156202818452
train loss:0.1097323959606468
train loss:0.06609227357774906
train loss:0.0542288015808577
train loss:0.19477760603416677
train loss:0.09295015254348954
train loss:0.3109248716472014
train loss:0.08089000828972204
train loss:0.11131160207353102
train loss:0.12938814501454896
train loss:0.16819455686015325
train loss:0.1502226975379533
train loss:0.13271782957050632
train loss:0.1562672179019871
train loss:0.12663107417262381
train loss:0.1375896908722974
train loss:0.13588813554261633
train loss:0.10691091351563514
train loss:0.12069699794607913
train loss:0.21072559179862815
train loss:0.12240244631422391
```

```
train loss:0.13247538645261522
train loss:0.15339973698950607
train loss:0.19819394448211664
train loss:0.15237452795533862
train loss:0.09374238705846812
train loss:0.11920911376265668
train loss:0.1430737992846992
train loss:0.22547810123288528
train loss:0.12885596550834355
train loss:0.07833673992175333
train loss:0.11604501131878386
train loss:0.11455462594096665
train loss:0.10224934259633629
train loss:0.09015098653354578
train loss:0.15071971853307103
train loss:0.11533252355002768
train loss:0.09703631638317933
train loss:0.14672138765681147
train loss:0.11729040639808015
train loss:0.1371165216036159
train loss:0.08022326339224152
train loss:0.06616064355000519
train loss:0.14836848989574813
train loss:0.09950583103651017
train loss:0.11742280207585891
train loss:0.08620334623101328
train loss:0.20363474886977953
train loss:0.14381878164452552
train loss:0.22177979692457014
train loss:0.13525598331732314
train loss:0.18016046220158516
train loss:0.12128616226355204
train loss:0.11524742896780488
train loss:0.15570969836951173
train loss:0.10735172661648162
train loss:0.06997443175671503
train loss:0.11570734151043734
train loss:0.1795568201140122
train loss:0.18159283725667122
train loss:0.09663673800748723
```

```
train loss:0.10163567994508062
train loss:0.10248434184994182
train loss:0.09956112068337523
train loss:0.1238891858666686
train loss:0.13595642287673285
train loss:0.1669459901184499
train loss:0.262147552959947
train loss:0.14592531193026015
train loss:0.14531983223463737
train loss:0.16873803977576354
train loss:0.16751655880418465
train loss:0.10764474135204342
train loss:0.13204929218323377
train loss:0.13054572638624332
train loss:0.18108493413483503
train loss:0.12054417075219652
train loss:0.14563009890181186
train loss:0.07067496022390501
train loss:0.19341400613079002
train loss:0.1284051221019942
train loss:0.16645897861108958
train loss:0.06611136396714629
train loss:0.10519623925818036
train loss:0.12813111132551513
train loss:0.1089423453842192
train loss:0.1353637772194844
train loss:0.14228005151936332
train loss:0.13780055760719748
train loss:0.11825163349840777
=============== Final Test Accuracy ===============
test acc:0.88575
Saved Network Parameters!
```