TypeB_AntsBees_VGG16_PyTorch_Training_5

January 6, 2022

1 Ants Bees VGG16

2 Fitting

3 TypeBTraining

[1]:
```
%pwd
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

[2]:
```
'''
3.
'''
import numpy as np
from PIL import Image
from torchvision import transforms
import matplotlib.pyplot as plt
import os
import torch
import torch.utils.data as data
from pathlib import Path
```

[3]:
```
torch.cuda.synchronize()
print(torch.cuda.memory_allocated())
```

```
0
```

[4]:
```
data_dir = '/content/gdrive/My Drive/Colab Notebooks/AntsBees/data'
root_dir= '/content/gdrive/My Drive/Colab Notebooks/AntsBees/data/
 ↪hymenoptera_data'
```

[5]:
```
os.chdir('/content/gdrive/My Drive/Colab Notebooks/AntsBees')
```

3.0.1 Device

[6]:
```
# (CPUGPU
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
cuda
```

4 (1) DataSet

4.0.1 train_list, val_list

[7]:
```
import glob
import pprint

def make_datapath_list(phase='train'):
    '''


    Parameters:
      phase(str): 'train''val'

    Returns:
      path_list(list):
    '''
    #
    #
    # rootpath +
    #   train/ants/*.jpg
    #   train/bees/*.jpg
    #   val/ants/*.jpg
    #   val/bees/*.jpg
    tt= phase +'/**/*.jpg'
    target_path = os.path.join(root_dir,tt)
    #
    path_list = []  #

    # glob()
    for path in glob.glob(target_path):
        path_list.append(path)

    return path_list

#
train_list = make_datapath_list(phase='train')
val_list = make_datapath_list(phase='val')
```

[8]:
```
print(train_list[4])
print(val_list[4])
```

```
/content/gdrive/My Drive/Colab
Notebooks/AntsBees/data/hymenoptera_data/train/ants/1099452230_d1949d3250.jpg
/content/gdrive/My Drive/Colab
Notebooks/AntsBees/data/hymenoptera_data/val/ants/1124525276_816a07c17f.jpg
```

[9]:
```
p=Path(train_list[5])
print(p.parts[-2])

p2=Path(val_list[-4])
print(p2.parts[-2])
```

```
ants
bees
```

5 DataSet

[10]:
```
from dsets.dsets import MakeDataset
from util.ImageTransform import ImageTransform
```

[11]:
```
'''
6.
'''
import torch

#
batch_size = 10
SIZE = 224
# RGB
MEAN = (0.485, 0.456, 0.406) # ImageNet
# RGB
STD = (0.229, 0.224, 0.225)  # ImageNet


#
size, mean, std = SIZE, MEAN, STD

# MakeDataset
train_dataset = MakeDataset(
    file_list=train_list, #
    transform=ImageTransform(size, mean, std), #
    phase='train')
# MakeDataset
val_dataset = MakeDataset(
    file_list=val_list, #
```

```
    transform=ImageTransform(size, mean, std), #
    phase='val')
```

[12]:
```
print(len(train_list))
print(len(val_list))
```

```
242
153
```

6 (2) DataLoader

[13]:
```
'''
6.
'''
from torch.utils.data import DataLoader

# :(, 3, 224, 224)
train_dl = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)

# :(, 3, 224, 224)
val_dl = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)
```

7 (4)

7.0.1

[14]:
```
from models.networks import network_vgg16
```

[15]:
```
'''
7. VGG16
'''
from torchvision import models
import torch.nn as nn

class Model():

  def __init__(self,save_dir,isTrain,use_cuda,continue_train,which_epoch=0):

    self.save_dir = save_dir
    self.isTrain = isTrain
    self.continue_train = continue_train
    self.use_cuda = use_cuda
    self.which_epoch = which_epoch

    if self.isTrain:
      self.model = network_vgg16()
      print('train')
```

```
      self.optimizer = torch.optim.SGD(self.model.parameters(), lr=0.
↪001,momentum=0.99)

      if not self.isTrain or self.continue_train:
        self.load_network(self.model,self.which_epoch)
        print('continued train')

  def load_network(self,network,which_epoch):
      save_filename = 'net_%s.pth' % (which_epoch)
      save_path = os.path.join(self.save_dir, save_filename)
      network.load_state_dict(torch.load(save_path))
      print('load network:',save_path)

  def train(self):
    self.model.train()

  def eval(self):
    self.model.eval()
```

[16]:
```
import os
print(os.getcwd())
```

```
/content/gdrive/My Drive/Colab Notebooks/AntsBees
```

[17]:
```
epoch_start=int(18)+1
epoch_end=epoch_start+4
epoch_end=epoch_start+4

for epoch_ndx in range(epoch_start,epoch_end):
  print(epoch_ndx)
```

```
19
20
21
22
```

[18]:
```
import pickle
from sklearn.metrics import accuracy_score
from tqdm import tqdm
import time

def pickle_dump(obj, path):
    with open(path, mode='wb') as f:
        pickle.dump(obj,f)

def pickle_load(path):
    with open(path, mode='rb') as f:
```

```
        data = pickle.load(f)
        return data

import torch.optim as optim

METRICS_LABEL_NDX=0
METRICS_PRED_NDX=1
METRICS_LOSS_NDX=2
METRICS_SIZE = 3


#
criterion = nn.CrossEntropyLoss()

#
#optimizer = optim.SGD(params=model.parameters(), lr=0.001, momentum=0.99)

metrics_dict = {'epoch_ndx':[],'phase':[],'loss/all':[],'loss/neg':[], 'loss/
 ↪pos':[],'correct/all':[],'correct/neg':[],'correct/pos':[],'pr/precision':
 ↪[],'pr/recall':[],'pr/f1_score':[]}

class Training:
  def␣
 ↪__init__(self,continue_train=True,which_epoch=0,how_much_epoch=4,save_freq=4):
 ↪
    #self.model=model(self.save_dir,self.isTrain,self.use_cuda,self.
 ↪continue_train,self.which_epoch)
    #self.optimizer=optim.SGD(params=self.model.parameters(), lr=0.001,␣
 ↪momentum=0.99)
    self.num_epochs=10
    self.batch_size=10
    self.use_cuda = True
    self.continue_train = continue_train
    self.isTrain = True
    #self.train_dl = train_dl
    #self.val_dl = val_dl
    self.device = torch.device("cuda" if self.use_cuda else "cpu")
    #self.augmentation_dict = opt.augmentation_dict
    self.save_dir = 'network'
    self.log_dir = 'logmetrics'
    self.how_much_epoch=how_much_epoch
    self.which_epoch=which_epoch
    self.save_freq = 4
    self.model=Model(self.save_dir,self.isTrain,self.use_cuda,self.
 ↪continue_train,self.which_epoch)
```

```
  self.metrics_dict = {'epoch_ndx':[],'phase':[],'loss/all':[],'loss/neg':[],␣
↪'loss/pos':[],'correct/all':[],'correct/neg':[],'correct/pos':[],'pr/
↪precision':[],'pr/recall':[],'pr/f1_score':[]}

 def main(self):
   t_epoch_start = time.time()
   if self.continue_train:
     epoch_start=int(self.which_epoch)+1
     epoch_end=epoch_start+self.how_much_epoch
   else:
     epoch_start=1
     epoch_end=epoch_start + self.how_much_epoch

   #metrics_dict = {'epoch_ndx':[],'phase':[],'loss/all':[],'loss/neg':[],␣
↪'loss/pos':[],'correct/all':[],'correct/neg':[],'correct/pos':[],'pr/
↪precision':[],'pr/recall':[],'pr/f1_score':[]}

   for epoch_ndx in range(epoch_start,epoch_end):

     # epoch=0
     print('----epoch:{}----'.format(epoch_ndx))
     trnMetrics_t = self.doTraining(epoch_ndx, train_dl)

     self.logMetrics(epoch_ndx, 'trn', trnMetrics_t)
     print('doTraining_end')

     valMetrics_t = self.doValidation(epoch_ndx, val_dl)
     self.logMetrics(epoch_ndx, 'val', valMetrics_t)
     print('doValidation_end')

     if epoch_ndx % self.save_freq == 0:
       print('saving the model at the end of epoch %d' % (epoch_ndx))
       self.save_network(self.model.model,epoch_ndx)
       print('saving the logMetrics at the end of epoch %d' % (epoch_ndx))
       self.save_file(self.metrics_dict,epoch_ndx)
   t_epoch_finish = time.time()

   print('timer:  {:.4f} sec.'.format(t_epoch_finish - t_epoch_start))


 def save_network(self, network, epoch_ndx, cpu=False):
     save_filename = 'net_%s.pth' % (epoch_ndx)
     save_path = os.path.join(self.save_dir, save_filename)
     torch.save(network.cpu().state_dict(), save_path)
     if not cpu and torch.cuda.is_available():
         network.cuda()
```

```
def save_file(self,logMetrics,epoch_ndx):
    save_filename = 'logMetrics_%s.pickle' % (epoch_ndx)
    save_path = os.path.join(self.log_dir, save_filename)
    with open(save_path, mode='wb') as f:
        pickle.dump(logMetrics,f)


def doTraining(self, epoch_ndx, train_dl):

  self.model.train()
  trnMetrics_g = torch.zeros(
          METRICS_SIZE,
          len(train_dl.dataset),
          device=self.device,
      )

  for batch_ndx, batch_tup in enumerate(tqdm(train_dl)):
    self.model.optimizer.zero_grad()

    loss_var = self.computeBatchLoss(
      batch_ndx,
      batch_tup,
      train_dl.batch_size,
      trnMetrics_g,)

    loss_var.backward()
    self.model.optimizer.step()

  return trnMetrics_g.to('cpu')

def doValidation(self, epoch_ndx, val_dl):
    with torch.no_grad():
        self.model.eval()
        valMetrics_g = torch.zeros(
            METRICS_SIZE,
            len(val_dl.dataset),
            device=self.device,
          )

        for batch_ndx, batch_tup in enumerate(tqdm(val_dl)):
            self.computeBatchLoss(
              batch_ndx,
              batch_tup,
              val_dl.batch_size,
              valMetrics_g,
            )
```

```
    return valMetrics_g.to('cpu')


def computeBatchLoss(self, batch_ndx, batch_tup, batch_size, metrics_g):

    input_t, label_t = batch_tup
    input_g = input_t.to(device)
    label_g = label_t.to(device)
    #model= self.model.to(device)

    outputs  = self.model.model(input_g)

    softmax = nn.Softmax(dim=1)
    prob_g= softmax(outputs)

    loss_func = nn.CrossEntropyLoss(reduction='none')
    loss_g = loss_func(outputs,label_g)

    start_ndx = batch_ndx * batch_size
    end_ndx = start_ndx + label_g.size()[0]

    metrics_g[0, start_ndx:end_ndx] = label_g
    metrics_g[1, start_ndx:end_ndx] = prob_g[:,1].detach()
    metrics_g[2, start_ndx:end_ndx] = loss_g.detach()

    return loss_g.mean()

#epoch
def logMetrics(self,epoch_ndx,phase,metrics_t):

    negLabel_mask = metrics_t[0] <= 0.5
    negPred_mask = metrics_t[1] <= 0.5

    posLabel_mask = ~negLabel_mask
    posPred_mask = ~negPred_mask

    neg_count = int(negLabel_mask.sum())
    pos_count = int(posLabel_mask.sum())

    trueNeg_count = neg_correct = int((negLabel_mask & negPred_mask).sum())
    truePos_count = pos_correct = int((posLabel_mask & posPred_mask).sum())

    falsePos_count = neg_count - neg_correct
    falseNeg_count = pos_count - pos_correct

    print('accuracy_all:{:.3f}'.format((pos_correct + neg_correct) /␣
↪metrics_t.shape[1] * 100))
```

```
        print('accuracy_neg:{:.3f}'.format((neg_correct) / neg_count * 100))
        print('accuracy_pos:{:.3f}'.format((pos_correct) / pos_count * 100))

        self.metrics_dict['phase'].append(phase)
        self.metrics_dict['epoch_ndx'].append(epoch_ndx)
        self.metrics_dict['loss/all'].append(metrics_t[METRICS_LOSS_NDX].mean().
↪item())
        self.metrics_dict['loss/neg'].append(metrics_t[METRICS_LOSS_NDX,␣
↪negLabel_mask].mean().item())
        self.metrics_dict['loss/pos'].append(metrics_t[METRICS_LOSS_NDX,␣
↪posLabel_mask].mean().item())

        self.metrics_dict['correct/all'].append((pos_correct + neg_correct) /␣
↪metrics_t.shape[1] * 100)
        self.metrics_dict['correct/neg'].append((neg_correct) / neg_count * 100)
        self.metrics_dict['correct/pos'].append((pos_correct) / pos_count * 100)

        self.metrics_dict['pr/precision'].append(truePos_count / np.
↪float32(truePos_count + falsePos_count))
        self.metrics_dict['pr/recall'].append(truePos_count / np.
↪float32(truePos_count + falseNeg_count))

        precision = truePos_count / np.float32(truePos_count + falsePos_count)
        recall = truePos_count / np.float32(truePos_count + falseNeg_count)

        self.metrics_dict['pr/f1_score'].append(2 * (precision * recall) /␣
↪(precision + recall))
```

8

[19]:
```
Training(continue_train=False,how_much_epoch=4,save_freq=4).main()
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to
/root/.cache/torch/hub/checkpoints/vgg16-397923af.pth

  0%|          | 0.00/528M [00:00<?, ?B/s]


classifier.6.weight
classifier.6.bias
train
----epoch:1----

100%|| 25/25 [00:32<00:00,  1.31s/it]
```

```
accuracy_all:79.752
accuracy_neg:77.869
accuracy_pos:81.667
doTraining_end

100%|| 16/16 [00:50<00:00,  3.18s/it]

accuracy_all:96.732
accuracy_neg:95.714
accuracy_pos:97.590
doValidation_end
----epoch:2----

100%|| 25/25 [00:02<00:00, 11.11it/s]

accuracy_all:93.388
accuracy_neg:90.984
accuracy_pos:95.833
doTraining_end

100%|| 16/16 [00:01<00:00, 10.12it/s]

accuracy_all:96.732
accuracy_neg:97.143
accuracy_pos:96.386
doValidation_end
----epoch:3----

100%|| 25/25 [00:02<00:00, 10.87it/s]

accuracy_all:94.628
accuracy_neg:94.262
accuracy_pos:95.000
doTraining_end

100%|| 16/16 [00:01<00:00, 10.78it/s]

accuracy_all:95.425
accuracy_neg:95.714
accuracy_pos:95.181
doValidation_end
----epoch:4----

100%|| 25/25 [00:02<00:00, 11.56it/s]

accuracy_all:97.934
accuracy_neg:98.361
accuracy_pos:97.500
doTraining_end
```

```
100%|| 16/16 [00:01<00:00, 10.80it/s]

accuracy_all:96.078
accuracy_neg:97.143
accuracy_pos:95.181
doValidation_end
saving the model at the end of epoch 4
saving the logMetrics at the end of epoch 4
timer:  104.4442 sec.
```

[20]:
```
with open('logmetrics/logMetrics_4.pickle','rb') as f:
  df=pickle.load(f)
print(df)
```

```
{'epoch_ndx': [1, 1, 2, 2, 3, 3, 4, 4], 'phase': ['trn', 'val', 'trn', 'val',
'trn', 'val', 'trn', 'val'], 'loss/all': [0.40094202756881714,
0.13093912601470947, 0.28687602281570435, 0.24209365248680115,
0.24475722014904022, 0.32391059398651123, 0.05987364053726196,
0.40586715936660767], 'loss/neg': [0.38867682218551636, 0.13716267049312592,
0.43134453892707825, 0.1936231106519699, 0.17015300691127777,
0.3132381737232208, 0.0359080545604229, 0.35760605335235596], 'loss/pos':
[0.4134116768836975, 0.12569034099578857, 0.13999976217746735,
0.28297239542007446, 0.3206048905849457, 0.3329114019870758,
0.08423865586519241, 0.4465693235397339], 'correct/all': [79.75206611570248,
96.73202614379085, 93.38842975206612, 96.73202614379085, 94.62809917355372,
95.42483660130719, 97.93388429752066, 96.07843137254902], 'correct/neg':
[77.8688524590164, 95.71428571428572, 90.98360655737704, 97.14285714285714,
94.26229508196722, 95.71428571428572, 98.36065573770492, 97.14285714285714],
'correct/pos': [81.66666666666667, 97.59036144578313, 95.83333333333334,
96.3855421686747, 95.0, 95.18072289156626, 97.5, 95.18072289156626],
'pr/precision': [0.784, 0.9642857142857143, 0.9126984126984127,
0.975609756097561, 0.9421487603305785, 0.9634146341463414, 0.9831932773109243,
0.9753086419753086], 'pr/recall': [0.8166666666666667, 0.9759036144578314,
0.9583333333333334, 0.963855421686747, 0.95, 0.9518072289156626, 0.975,
0.9518072289156626], 'pr/f1_score': [0.7999999999999999, 0.970059880239521,
0.9349593495934959, 0.9696969696969697, 0.946058091286307, 0.9575757575757576,
0.9790794979079498, 0.9634146341463414]}
```

9

9.0.1 epoch=4epoch=4

[ ]:
```
Training(continue_train=True,which_epoch=4,how_much_epoch=4,save_freq=4).main()
```

```
classifier.6.weight
classifier.6.bias
train
```

```
load network: network/net_4.pth
continued train
----epoch:5----

100%|| 25/25 [00:02<00:00,  9.08it/s]

accuracy_all:97.531
accuracy_neg:98.361
accuracy_pos:96.694
doTraining_end

100%|| 16/16 [00:01<00:00,  9.70it/s]

accuracy_all:97.386
accuracy_neg:97.143
accuracy_pos:97.590
doValidation_end
----epoch:6----

100%|| 25/25 [00:02<00:00, 10.45it/s]

accuracy_all:96.296
accuracy_neg:95.082
accuracy_pos:97.521
doTraining_end

100%|| 16/16 [00:01<00:00,  9.91it/s]

accuracy_all:96.078
accuracy_neg:97.143
accuracy_pos:95.181
doValidation_end
----epoch:7----

100%|| 25/25 [00:02<00:00, 10.48it/s]

accuracy_all:96.708
accuracy_neg:95.902
accuracy_pos:97.521
doTraining_end

100%|| 16/16 [00:01<00:00,  9.91it/s]

accuracy_all:95.425
accuracy_neg:97.143
accuracy_pos:93.976
doValidation_end
----epoch:8----

100%|| 25/25 [00:02<00:00, 10.47it/s]
```

```
accuracy_all:97.119
accuracy_neg:98.361
accuracy_pos:95.868
doTraining_end

100%|| 16/16 [00:01<00:00,  9.68it/s]

accuracy_all:95.425
accuracy_neg:97.143
accuracy_pos:93.976
doValidation_end
saving the model at the end of epoch 8
saving the logMetrics at the end of epoch 8
timer:  21.6169 sec.
```

[ ]:
```
with open('logmetrics/logMetrics_8.pickle','rb') as f:
  df=pickle.load(f)
print(df)
```

```
{'epoch_ndx': [5, 5, 6, 6, 7, 7, 8, 8], 'phase': ['trn', 'val', 'trn', 'val',
'trn', 'val', 'trn', 'val'], 'loss/all': [0.1609499156475067,
0.20080764591693878, 0.1757982224225998, 0.2455892413854599,
0.20594224333763123, 0.27826085686683655, 0.22360025346279144,
0.3226856291294098], 'loss/neg': [0.05199730023741722, 0.26429373025894165,
0.2661421000957489, 0.1592920571565628, 0.18748317658901215,
0.11170906573534012, 0.02784634754061699, 0.03173687681555748], 'loss/pos':
[0.27080294489860535, 0.14726516604423523, 0.08470767736434937,
0.3183700442314148, 0.22455385327339172, 0.4187261760234833,
0.42097198963165283, 0.5680640935897827], 'correct/all': [97.53086419753086,
97.38562091503267, 96.29629629629629, 96.07843137254902, 96.70781893004116,
95.42483660130719, 97.11934156378601, 95.42483660130719], 'correct/neg':
[98.36065573770492, 97.14285714285714, 95.08196721311475, 97.14285714285714,
95.90163934426229, 97.14285714285714, 98.36065573770492, 97.14285714285714],
'correct/pos': [96.69421487603306, 97.59036144578313, 97.52066115702479,
95.18072289156626, 97.52066115702479, 93.97590361445783, 95.86776859504133,
93.97590361445783], 'pr/precision': [0.9831932773109243, 0.9759036144578314,
0.9516129032258065, 0.9753086419753086, 0.959349593495935, 0.975,
0.9830508474576272, 0.975], 'pr/recall': [0.9669421487603306,
0.9759036144578314, 0.9752066115702479, 0.9518072289156626, 0.9752066115702479,
0.9397590361445783, 0.9586776859504132, 0.9397590361445783], 'pr/f1_score':
[0.975, 0.9759036144578314, 0.963265306122449, 0.9634146341463414,
0.9672131147540983, 0.9570552147239264, 0.9707112970711298, 0.9570552147239264]}
```

9.0.2 epoch=8epoch=4

[ ]:
```
Training(continue_train=True,which_epoch=8,how_much_epoch=4,save_freq=4).main()
```

```
classifier.6.weight
classifier.6.bias
train
load network: network/net_8.pth
continued train
----epoch:9----

100%|| 25/25 [00:02<00:00,  8.94it/s]

accuracy_all:93.827
accuracy_neg:94.262
accuracy_pos:93.388
doTraining_end

100%|| 16/16 [00:01<00:00,  8.00it/s]

accuracy_all:96.732
accuracy_neg:97.143
accuracy_pos:96.386
doValidation_end
----epoch:10----

100%|| 25/25 [00:02<00:00, 10.01it/s]

accuracy_all:95.885
accuracy_neg:94.262
accuracy_pos:97.521
doTraining_end

100%|| 16/16 [00:01<00:00,  9.81it/s]

accuracy_all:96.078
accuracy_neg:98.571
accuracy_pos:93.976
doValidation_end
----epoch:11----

100%|| 25/25 [00:02<00:00, 10.51it/s]

accuracy_all:95.885
accuracy_neg:94.262
accuracy_pos:97.521
doTraining_end

100%|| 16/16 [00:01<00:00,  9.67it/s]

accuracy_all:95.425
accuracy_neg:97.143
accuracy_pos:93.976
doValidation_end
----epoch:12----
```

```
100%|| 25/25 [00:02<00:00, 10.49it/s]

accuracy_all:95.062
accuracy_neg:95.082
accuracy_pos:95.041
doTraining_end

100%|| 16/16 [00:01<00:00,  9.93it/s]

accuracy_all:94.118
accuracy_neg:91.429
accuracy_pos:96.386
doValidation_end
saving the model at the end of epoch 12
saving the logMetrics at the end of epoch 12
timer:  22.6314 sec.
```

[ ]:
```
with open('logmetrics/logMetrics_12.pickle','rb') as f:
  df=pickle.load(f)
print(df)
```

```
{'epoch_ndx': [9, 9, 10, 10, 11, 11, 12, 12], 'phase': ['trn', 'val', 'trn',
'val', 'trn', 'val', 'trn', 'val'], 'loss/all': [0.36907994747161865,
0.2484544813632965, 0.1876516342163086, 0.3539607524871826, 0.3026646375656128,
0.3448130190372467, 0.19308461248874664, 0.48201218247413635], 'loss/neg':
[0.37759295105934143, 0.14485757052898407, 0.15945252776145935,
0.08252274245023727, 0.3223026394844055, 0.14392654597759247,
0.13487133383750916, 0.9317216277122498], 'loss/pos': [0.36049649119377136,
0.3358253836631775, 0.21608377993106842, 0.5828843116760254, 0.2828643023967743,
0.5142353773117065, 0.2517789602279663, 0.10273918509483337], 'correct/all':
[93.82716049382715, 96.73202614379085, 95.88477366255144, 96.07843137254902,
95.88477366255144, 95.42483660130719, 95.06172839506173, 94.11764705882352],
'correct/neg': [94.26229508196722, 97.14285714285714, 94.26229508196722,
98.57142857142858, 94.26229508196722, 97.14285714285714, 95.08196721311475,
91.42857142857143], 'correct/pos': [93.38842975206612, 96.3855421686747,
97.52066115702479, 93.97590361445783, 97.52066115702479, 93.97590361445783,
95.0413223140496, 96.3855421686747], 'pr/precision': [0.9416666666666667,
0.975609756097561, 0.944, 0.9873417721518988, 0.944, 0.975, 0.9504132231404959,
0.9302325581395349], 'pr/recall': [0.9338842975206612, 0.963855421686747,
0.9752066115702479, 0.9397590361445783, 0.9752066115702479, 0.9397590361445783,
0.9504132231404959, 0.963855421686747], 'pr/f1_score': [0.9377593360995851,
0.9696969696969697, 0.959349593495935, 0.962962962962963, 0.959349593495935,
0.9570552147239264, 0.9504132231404959, 0.9467455621301776]}
```

9.0.3 epoch=12epoch=4

[ ]:
```
Training(continue_train=True,which_epoch=12,how_much_epoch=4,save_freq=4).main()
```

```
classifier.6.weight
classifier.6.bias
train
load network: network/net_12.pth
continued train
----epoch:13----

100%|| 25/25 [00:02<00:00,  8.83it/s]

accuracy_all:94.650
accuracy_neg:92.623
accuracy_pos:96.694
doTraining_end

100%|| 16/16 [00:01<00:00,  9.31it/s]

accuracy_all:95.425
accuracy_neg:95.714
accuracy_pos:95.181
doValidation_end
----epoch:14----

100%|| 25/25 [00:02<00:00, 10.36it/s]

accuracy_all:97.531
accuracy_neg:100.000
accuracy_pos:95.041
doTraining_end

100%|| 16/16 [00:01<00:00,  9.79it/s]

accuracy_all:95.425
accuracy_neg:95.714
accuracy_pos:95.181
doValidation_end
----epoch:15----

100%|| 25/25 [00:02<00:00, 10.39it/s]

accuracy_all:97.531
accuracy_neg:97.541
accuracy_pos:97.521
doTraining_end

100%|| 16/16 [00:01<00:00,  9.95it/s]
```

```
accuracy_all:95.425
accuracy_neg:94.286
accuracy_pos:96.386
doValidation_end
----epoch:16----

100%|| 25/25 [00:02<00:00, 10.39it/s]

accuracy_all:96.296
accuracy_neg:94.262
accuracy_pos:98.347
doTraining_end

100%|| 16/16 [00:01<00:00,  9.66it/s]

accuracy_all:96.732
accuracy_neg:97.143
accuracy_pos:96.386
doValidation_end
saving the model at the end of epoch 16
saving the logMetrics at the end of epoch 16
timer:  22.4728 sec.
```

[ ]:
```
with open('logmetrics/logMetrics_16.pickle','rb') as f:
  df=pickle.load(f)
print(df)
```

```
{'epoch_ndx': [13, 13, 14, 14, 15, 15, 16, 16], 'phase': ['trn', 'val', 'trn',
'val', 'trn', 'val', 'trn', 'val'], 'loss/all': [0.17611442506313324,
0.42756667733192444, 0.18896250426769257, 0.4184344410896301,
0.17619943618774414, 0.3917209506034851, 0.22786182165145874,
0.33452412486076355], 'loss/neg': [0.30494746565818787, 0.3738877475261688,
0.007854694500565529, 0.3287510871887207, 0.08537153899669647,
0.4419246017932892, 0.368407666683197, 0.1835719794034958], 'loss/pos':
[0.04621664434671402, 0.4728381037712097, 0.37156710028648376,
0.49407094717025757, 0.2677779793739319, 0.3493804335594177,
0.08615443855524063, 0.4618331789970398], 'correct/all': [94.65020576131687,
95.42483660130719, 97.53086419753086, 95.42483660130719, 97.53086419753086,
95.42483660130719, 96.29629629629629, 96.73202614379085], 'correct/neg':
[92.62295081967213, 95.71428571428572, 100.0, 95.71428571428572,
97.54098360655738, 94.28571428571428, 94.26229508196722, 97.14285714285714],
'correct/pos': [96.69421487603306, 95.18072289156626, 95.0413223140496,
95.18072289156626, 97.52066115702479, 96.3855421686747, 98.34710743801654,
96.3855421686747], 'pr/precision': [0.9285714285714286, 0.9634146341463414, 1.0,
0.9634146341463414, 0.9752066115702479, 0.9523809523809523, 0.9444444444444444,
0.975609756097561], 'pr/recall': [0.9669421487603306, 0.9518072289156626,
0.9504132231404959, 0.9518072289156626, 0.9752066115702479, 0.963855421686747,
0.9834710743801653, 0.963855421686747], 'pr/f1_score': [0.9473684210526316,
0.9575757575757576, 0.9745762711864406, 0.9575757575757576, 0.9752066115702479,
0.9580838323353292, 0.9635627530364373, 0.9696969696969697]}
```

9.0.4 epoch=16epoch=4

[ ]:
```
Training(continue_train=True,which_epoch=16,how_much_epoch=4,save_freq=4).main()
```

```
classifier.6.weight
classifier.6.bias
train
load network: network/net_16.pth
continued train
----epoch:17----

100%|| 25/25 [00:02<00:00,  9.14it/s]

accuracy_all:96.296
accuracy_neg:95.902
accuracy_pos:96.694
doTraining_end

100%|| 16/16 [00:01<00:00,  8.55it/s]

accuracy_all:96.732
accuracy_neg:97.143
accuracy_pos:96.386
doValidation_end
----epoch:18----

100%|| 25/25 [00:02<00:00,  9.76it/s]

accuracy_all:97.942
accuracy_neg:99.180
accuracy_pos:96.694
doTraining_end

100%|| 16/16 [00:01<00:00,  9.83it/s]

accuracy_all:95.425
accuracy_neg:97.143
accuracy_pos:93.976
doValidation_end
----epoch:19----

100%|| 25/25 [00:02<00:00, 10.40it/s]

accuracy_all:96.296
accuracy_neg:95.902
accuracy_pos:96.694
doTraining_end

100%|| 16/16 [00:01<00:00,  9.90it/s]
```

```
accuracy_all:97.386
accuracy_neg:97.143
accuracy_pos:97.590
doValidation_end
----epoch:20----
```

```
100%|| 25/25 [00:02<00:00, 10.29it/s]
```

```
accuracy_all:95.062
accuracy_neg:95.082
accuracy_pos:95.041
doTraining_end
```

```
100%|| 16/16 [00:01<00:00,  9.65it/s]
```

```
accuracy_all:97.386
accuracy_neg:97.143
accuracy_pos:97.590
doValidation_end
saving the model at the end of epoch 20
saving the logMetrics at the end of epoch 20
timer:  22.6043 sec.
```

10 logMetrics.pickle

[ ]:
```
import glob
pickle_files=glob.glob('logmetrics/*.pickle')
```

[ ]:
```
print(pickle_files)
```

```
['logmetrics/logMetrics_4.pickle', 'logmetrics/logMetrics_8.pickle',
'logmetrics/logMetrics_12.pickle', 'logmetrics/logMetrics_16.pickle',
'logmetrics/logMetrics_20.pickle']
```

[ ]:
```
import pickle
import pandas as pd

metrics_list=[]
for file in pickle_files:
  with open(file,'rb') as f:
    d=pickle.load(f)
    df=pd.DataFrame(d)
    metrics_list.append(df)

print(metrics_list)
df=pd.concat(metrics_list,axis=0)

display(df)
```

```
[   epoch_ndx phase  loss/all  ...  pr/precision  pr/recall  pr/f1_score
0           1   trn  0.352068  ...      0.838983   0.818182     0.828452
1           1   val  0.150938  ...      0.962963   0.939759     0.951220
2           2   trn  0.199374  ...      0.951220   0.966942     0.959016
3           2   val  0.193100  ...      0.941860   0.975904     0.958580
4           3   trn  0.245235  ...      0.957983   0.942149     0.950000
5           3   val  0.199039  ...      0.963855   0.963855     0.963855
6           4   trn  0.237065  ...      0.929688   0.983471     0.955823
7           4   val  0.239174  ...      0.975309   0.951807     0.963415

[8 rows x 11 columns],    epoch_ndx phase  loss/all  ...  pr/precision
pr/recall  pr/f1_score
0           5   trn  0.160950  ...      0.983193   0.966942     0.975000
1           5   val  0.200808  ...      0.975904   0.975904     0.975904
2           6   trn  0.175798  ...      0.951613   0.975207     0.963265
3           6   val  0.245589  ...      0.975309   0.951807     0.963415
4           7   trn  0.205942  ...      0.959350   0.975207     0.967213
5           7   val  0.278261  ...      0.975000   0.939759     0.957055
6           8   trn  0.223600  ...      0.983051   0.958678     0.970711
7           8   val  0.322686  ...      0.975000   0.939759     0.957055

[8 rows x 11 columns],    epoch_ndx phase  loss/all  ...  pr/precision
pr/recall  pr/f1_score
0           9   trn  0.369080  ...      0.941667   0.933884     0.937759
1           9   val  0.248454  ...      0.975610   0.963855     0.969697
2          10   trn  0.187652  ...      0.944000   0.975207     0.959350
3          10   val  0.353961  ...      0.987342   0.939759     0.962963
4          11   trn  0.302665  ...      0.944000   0.975207     0.959350
5          11   val  0.344813  ...      0.975000   0.939759     0.957055
6          12   trn  0.193085  ...      0.950413   0.950413     0.950413
7          12   val  0.482012  ...      0.930233   0.963855     0.946746

[8 rows x 11 columns],    epoch_ndx phase  loss/all  ...  pr/precision
pr/recall  pr/f1_score
0          13   trn  0.176114  ...      0.928571   0.966942     0.947368
1          13   val  0.427567  ...      0.963415   0.951807     0.957576
2          14   trn  0.188963  ...      1.000000   0.950413     0.974576
3          14   val  0.418434  ...      0.963415   0.951807     0.957576
4          15   trn  0.176199  ...      0.975207   0.975207     0.975207
5          15   val  0.391721  ...      0.952381   0.963855     0.958084
6          16   trn  0.227862  ...      0.944444   0.983471     0.963563
7          16   val  0.334524  ...      0.975610   0.963855     0.969697

[8 rows x 11 columns],    epoch_ndx phase  loss/all  ...  pr/precision
pr/recall  pr/f1_score
0          17   trn  0.178282  ...      0.959016   0.966942     0.962963
1          17   val  0.310000  ...      0.975610   0.963855     0.969697
2          18   trn  0.070202  ...      0.991525   0.966942     0.979079
```

```
3         18   val  0.285968  ...      0.975000   0.939759     0.957055
4         19   trn  0.186429  ...      0.959016   0.966942     0.962963
5         19   val  0.187677  ...      0.975904   0.975904     0.975904
6         20   trn  0.192381  ...      0.950413   0.950413     0.950413
7         20   val  0.200543  ...      0.975904   0.975904     0.975904

[8 rows x 11 columns]]

   epoch_ndx phase  loss/all  ...  pr/precision  pr/recall  pr/f1_score
0          1   trn  0.352068  ...      0.838983   0.818182     0.828452
1          1   val  0.150938  ...      0.962963   0.939759     0.951220
2          2   trn  0.199374  ...      0.951220   0.966942     0.959016
3          2   val  0.193100  ...      0.941860   0.975904     0.958580
4          3   trn  0.245235  ...      0.957983   0.942149     0.950000
5          3   val  0.199039  ...      0.963855   0.963855     0.963855
6          4   trn  0.237065  ...      0.929688   0.983471     0.955823
7          4   val  0.239174  ...      0.975309   0.951807     0.963415
0          5   trn  0.160950  ...      0.983193   0.966942     0.975000
1          5   val  0.200808  ...      0.975904   0.975904     0.975904
2          6   trn  0.175798  ...      0.951613   0.975207     0.963265
3          6   val  0.245589  ...      0.975309   0.951807     0.963415
4          7   trn  0.205942  ...      0.959350   0.975207     0.967213
5          7   val  0.278261  ...      0.975000   0.939759     0.957055
6          8   trn  0.223600  ...      0.983051   0.958678     0.970711
7          8   val  0.322686  ...      0.975000   0.939759     0.957055
0          9   trn  0.369080  ...      0.941667   0.933884     0.937759
1          9   val  0.248454  ...      0.975610   0.963855     0.969697
2         10   trn  0.187652  ...      0.944000   0.975207     0.959350
3         10   val  0.353961  ...      0.987342   0.939759     0.962963
4         11   trn  0.302665  ...      0.944000   0.975207     0.959350
5         11   val  0.344813  ...      0.975000   0.939759     0.957055
6         12   trn  0.193085  ...      0.950413   0.950413     0.950413
7         12   val  0.482012  ...      0.930233   0.963855     0.946746
0         13   trn  0.176114  ...      0.928571   0.966942     0.947368
1         13   val  0.427567  ...      0.963415   0.951807     0.957576
2         14   trn  0.188963  ...      1.000000   0.950413     0.974576
3         14   val  0.418434  ...      0.963415   0.951807     0.957576
4         15   trn  0.176199  ...      0.975207   0.975207     0.975207
5         15   val  0.391721  ...      0.952381   0.963855     0.958084
6         16   trn  0.227862  ...      0.944444   0.983471     0.963563
7         16   val  0.334524  ...      0.975610   0.963855     0.969697
0         17   trn  0.178282  ...      0.959016   0.966942     0.962963
1         17   val  0.310000  ...      0.975610   0.963855     0.969697
2         18   trn  0.070202  ...      0.991525   0.966942     0.979079
3         18   val  0.285968  ...      0.975000   0.939759     0.957055
4         19   trn  0.186429  ...      0.959016   0.966942     0.962963
5         19   val  0.187677  ...      0.975904   0.975904     0.975904
6         20   trn  0.192381  ...      0.950413   0.950413     0.950413
```

```
7         20    val  0.200543  ...      0.975904   0.975904     0.975904

[40 rows x 11 columns]
```

[ ]:
```
history_train=df.loc[df['phase']=='trn']
history_val=df.loc[df['phase']=='val']
first_train=df.loc[df['epoch_ndx']==1]
print(first_train)

key1=df['epoch_ndx']==5
key2=df['phase']=='trn'
key=key1&key2
print(key)
```

```
   epoch_ndx phase  loss/all  ...  pr/precision  pr/recall  pr/f1_score
0          1   trn  0.352068  ...      0.838983   0.818182     0.828452
1          1   val  0.150938  ...      0.962963   0.939759     0.951220

[2 rows x 11 columns]
0    False
1    False
2    False
3    False
4    False
5    False
6    False
7    False
0     True
1    False
2    False
3    False
4    False
5    False
6    False
7    False
0    False
1    False
2    False
3    False
4    False
5    False
6    False
7    False
0    False
1    False
2    False
3    False
```

```
4    False
5    False
6    False
7    False
0    False
1    False
2    False
3    False
4    False
5    False
6    False
7    False
dtype: bool
```

[ ]:
```
correct_all=df.loc[(df['epoch_ndx']==5)&(df['phase']=='trn'),'correct/all']
print(correct_all)
```

```
0    97.530864
Name: correct/all, dtype: float64
```

[ ]:
```
display(history_train)
display(history_val)
```

	epoch_ndx	phase	loss/all	...	pr/precision	pr/recall	pr/f1_score
0	1	trn	0.352068	...	0.838983	0.818182	0.828452
2	2	trn	0.199374	...	0.951220	0.966942	0.959016
4	3	trn	0.245235	...	0.957983	0.942149	0.950000
6	4	trn	0.237065	...	0.929688	0.983471	0.955823
0	5	trn	0.160950	...	0.983193	0.966942	0.975000
2	6	trn	0.175798	...	0.951613	0.975207	0.963265
4	7	trn	0.205942	...	0.959350	0.975207	0.967213
6	8	trn	0.223600	...	0.983051	0.958678	0.970711
0	9	trn	0.369080	...	0.941667	0.933884	0.937759
2	10	trn	0.187652	...	0.944000	0.975207	0.959350
4	11	trn	0.302665	...	0.944000	0.975207	0.959350
6	12	trn	0.193085	...	0.950413	0.950413	0.950413
0	13	trn	0.176114	...	0.928571	0.966942	0.947368
2	14	trn	0.188963	...	1.000000	0.950413	0.974576
4	15	trn	0.176199	...	0.975207	0.975207	0.975207
6	16	trn	0.227862	...	0.944444	0.983471	0.963563
0	17	trn	0.178282	...	0.959016	0.966942	0.962963
2	18	trn	0.070202	...	0.991525	0.966942	0.979079
4	19	trn	0.186429	...	0.959016	0.966942	0.962963
6	20	trn	0.192381	...	0.950413	0.950413	0.950413

[20 rows x 11 columns]

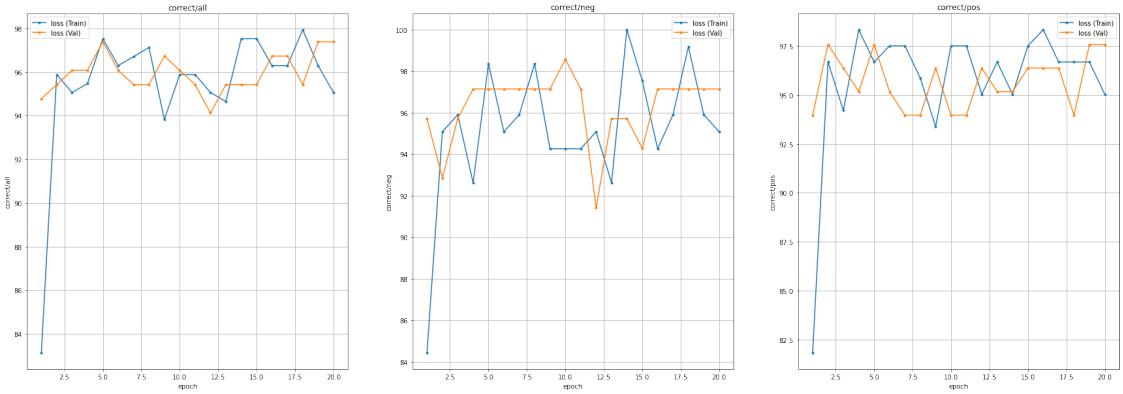
```
   epoch_ndx phase  loss/all  ...  pr/precision  pr/recall  pr/f1_score
1          1   val  0.150938  ...      0.962963   0.939759     0.951220
3          2   val  0.193100  ...      0.941860   0.975904     0.958580
5          3   val  0.199039  ...      0.963855   0.963855     0.963855
7          4   val  0.239174  ...      0.975309   0.951807     0.963415
1          5   val  0.200808  ...      0.975904   0.975904     0.975904
3          6   val  0.245589  ...      0.975309   0.951807     0.963415
5          7   val  0.278261  ...      0.975000   0.939759     0.957055
7          8   val  0.322686  ...      0.975000   0.939759     0.957055
1          9   val  0.248454  ...      0.975610   0.963855     0.969697
3         10   val  0.353961  ...      0.987342   0.939759     0.962963
5         11   val  0.344813  ...      0.975000   0.939759     0.957055
7         12   val  0.482012  ...      0.930233   0.963855     0.946746
1         13   val  0.427567  ...      0.963415   0.951807     0.957576
3         14   val  0.418434  ...      0.963415   0.951807     0.957576
5         15   val  0.391721  ...      0.952381   0.963855     0.958084
7         16   val  0.334524  ...      0.975610   0.963855     0.969697
1         17   val  0.310000  ...      0.975610   0.963855     0.969697
3         18   val  0.285968  ...      0.975000   0.939759     0.957055
5         19   val  0.187677  ...      0.975904   0.975904     0.975904
7         20   val  0.200543  ...      0.975904   0.975904     0.975904

[20 rows x 11 columns]
```

[ ]:
```
print(type(history_train['epoch_ndx']))
```

```
<class 'pandas.core.series.Series'>
```

[ ]:
```
import matplotlib.pyplot as plt
%matplotlib inline


fig,(ax1,ax2,ax3)=plt.subplots(1,3,figsize=(30,10))

# correct/all
ax1.plot(history_train['epoch_ndx'],history_train['correct/all'],
         marker='.',
         label='loss (Train)')
ax1.plot(history_val['epoch_ndx'],history_val['correct/all'],
         marker='.',
         label='loss (Val)')
ax1.legend(loc='best')
ax1.grid()
ax1.set_title('correct/all')
ax1.set_xlabel('epoch')
ax1.set_ylabel('correct/all')
```

```
# correct/all
ax2.plot(history_train['epoch_ndx'],history_train['correct/neg'],
         marker='.',
         label='loss (Train)')
ax2.plot(history_val['epoch_ndx'],history_val['correct/neg'],
         marker='.',
         label='loss (Val)')
ax2.legend(loc='best')
ax2.grid()
ax2.set_title('correct/neg')
ax2.set_xlabel('epoch')
ax2.set_ylabel('correct/neg')

# correct/all
ax3.plot(history_train['epoch_ndx'],history_train['correct/pos'],
         marker='.',
         label='loss (Train)')
ax3.plot(history_val['epoch_ndx'],history_val['correct/pos'],
         marker='.',
         label='loss (Val)')
ax3.legend(loc='best')
ax3.grid()
ax3.set_title('correct/pos')
ax3.set_xlabel('epoch')
ax3.set_ylabel('correct/pos')


plt.show()
```

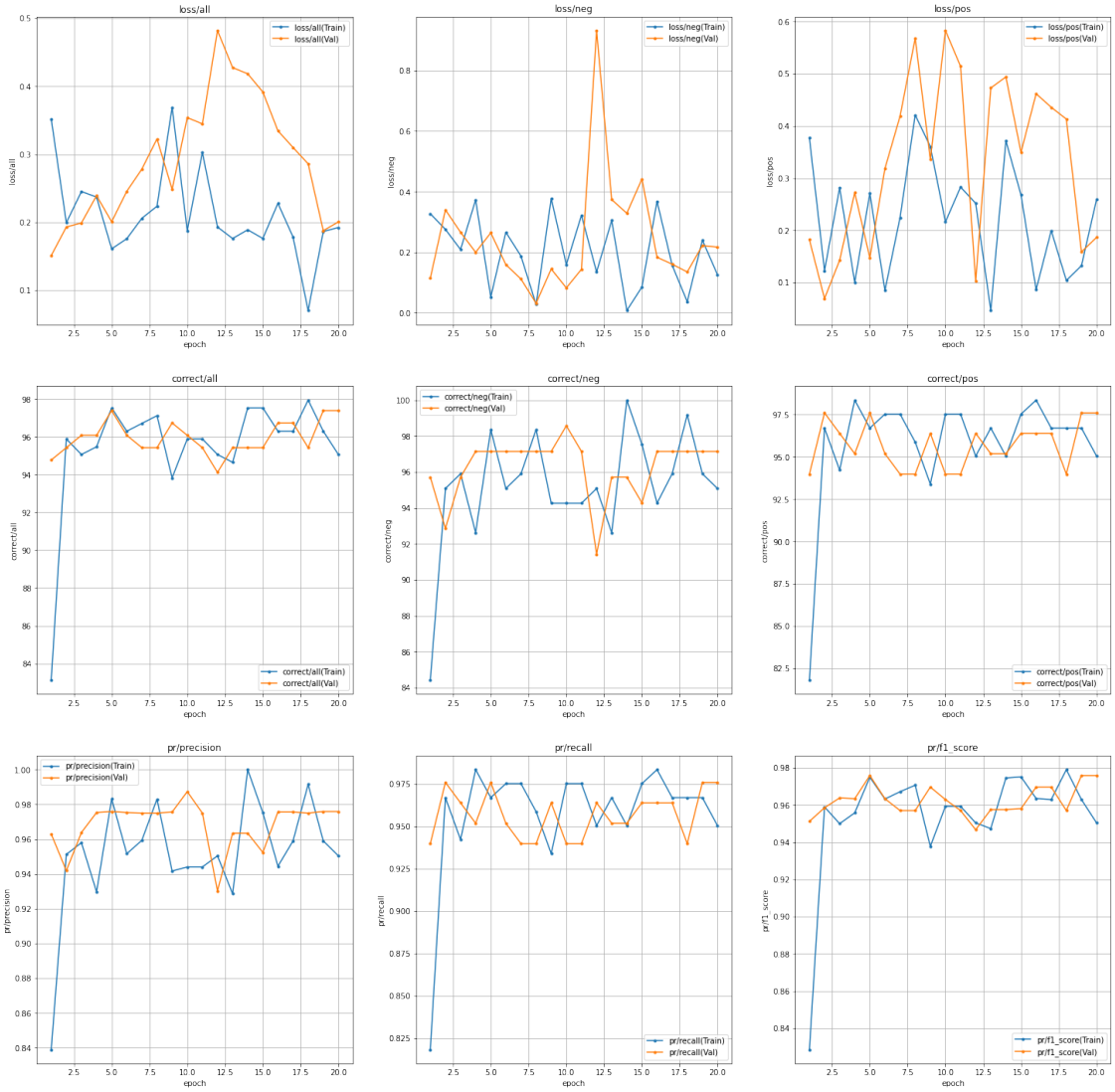


11 For Loop

[ ]:
```
name=df.columns.to_list()
print(name)

pop_list=[0,1]

for i in sorted(pop_list, reverse=True):
  name.pop(i)

print(name)
```

```
['epoch_ndx', 'phase', 'loss/all', 'loss/neg', 'loss/pos', 'correct/all',
'correct/neg', 'correct/pos', 'pr/precision', 'pr/recall', 'pr/f1_score']
['loss/all', 'loss/neg', 'loss/pos', 'correct/all', 'correct/neg',
'correct/pos', 'pr/precision', 'pr/recall', 'pr/f1_score']
```

[ ]:
```
fig=plt.figure(figsize=(25,25))

for i in range(9):
  ax=fig.add_subplot(3,3,i+1)
  ax.plot(history_train['epoch_ndx'],history_train[name[i]],
          marker='.',
          label=name[i] +'(Train)')
  ax.plot(history_val['epoch_ndx'],history_val[name[i]],
          marker='.',
          label=name[i] +'(Val)')
  ax.legend(loc='best')
  ax.grid()
  ax.set_title(name[i])
  ax.set_xlabel('epoch')
  ax.set_ylabel(name[i])

figname = 'result/evaluation.png'
fig.savefig(figname,bbox_inches='tight')


plt.show()
```


loss/all
loss/all(Train)
loss/all(Val)
loss/all
epoch
loss/neg
loss/neg(Train)
loss/neg(Val)
loss/neg
epoch
loss/pos
loss/pos(Train)
loss/pos(Val)
loss/pos
epoch
correct/all
correct/all(Train)
correct/all(Val)
correct/all
epoch
correct/neg
correct/neg(Train)
correct/neg(Val)
correct/neg
epoch
correct/pos
correct/pos(Train)
correct/pos(Val)
correct/pos
epoch
pr/precision
pr/precision(Train)
pr/precision(Val)
pr/precision
epoch
pr/recall
pr/recall(Train)
pr/recall(Val)
pr/recall
epoch
pr/f1_score
pr/f1_score(Train)
pr/f1_score(Val)
pr/f1_score
epoch

12 END