Report of TP2

IFT6758-A-A18 - Science des données

Team Members

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1. Question 1 Competition of Classification

Answer

To accomplish the competition, we will train several simple residual convolutional neural networks on training dataset and verify their performance on validation dataset, which is split from the whole training dataset. Then, we will use these well trained networks to make prediction on the test dataset. Finally, we make an ensemble prediction using bagging. We save our final prediction in a csv file with each line has a integer 0 or 1 representing the class label of the respective example line in the test dataset.

1.1 GPU support on Colab.

Colab computation platform accelerates our training process.

In [1]:

```
# instruction of using colab python
# https://medium.com/deep-learning-turkey/google-colab-free-gpu-tutorial-e113627
b9f5d

from os.path import exists
from wheel.pep425tags import get_abbr_impl, get_impl_ver, get_abi_tag
platform = '{}{}-{}'.format(get_abbr_impl(), get_impl_ver(), get_abi_tag())
cuda_output = !ldconfig -p|grep cudart.so|sed -e 's/.*\.\([0-9]*\)\.\([0-9]*\)$/
cu\1\2/'
accelerator = cuda_output[0] if exists('/dev/nvidia0') else 'cpu'

!pip install -q http://download.pytorch.org/whl/{accelerator}/torch-0.4.1-{platf
orm}-linux_x86_64.whl torchvision
import torch
```

```
tcmalloc: large alloc 1073750016 bytes == 0x58792000 @  0x7fc70bc04
2a4 0x591a07 0x5b5d56 0x502e9a 0x506859 0x502209 0x502f3d 0x506859
0x504c28 0x502540 0x502f3d 0x506859 0x504c28 0x502540 0x502f3d 0x50
6859 0x504c28 0x502540 0x502f3d 0x507641 0x502209 0x502f3d 0x506859
0x504c28 0x502540 0x502f3d 0x507641 0x504c28 0x502540 0x502f3d 0x50
7641
```

In [2]:

```
from google.colab import drive
drive.mount('/content/drive/')
# 4/oQAe5a98SL9kZzGrY2QyFGlcPFGy4wN4gZZ1O8R4y4zXhhJWJ0KnGT4
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/a
uth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.go
ogleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoo
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.tes
t%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2
Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2F
www.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive/
```

In [3]:

```
import os
os.chdir("drive/My Drive/Colab Notebooks/IFT6758/TP2/")
#check if you are in the right directory
!ls
```

```
 Codes_HW4_IFT6390_Final.ipynb
'IFT3700 et IFT6758 Automne 2018  Travail 2 francais.pdf'
 models
 PATCH.amat
 PATCH_test.amat
 qestion1.ipynb
 question1b.ipynb
 Report_TP2_20181220.ipynb
 Report_TP2_20181221.ipynb
 submission_bagging_models.csv
 submissions
```

1.2 modules

In [4]:

```
import numpy as np
from __future__ import print_function, division
import matplotlib.pyplot as plt
%matplotlib inline
import time
import os
import copy
import sys
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.optim import lr_scheduler
import torchvision
from scipy.ndimage import rotate
import random

# use GPU as priority if available
if torch.cuda.is_available():
    device = torch.device('cuda')
    use_cuda = True
else:
    device = torch.device('cpu')
    use_cuda = False

torch.set_default_tensor_type(torch.DoubleTensor)
print(device)
```

cuda

In [0]:

```
# We built two functions: `debug` and `print_progress` for debugging during
# development and show training progress respectively.

DEBUG = True
def debug(*args, **kwargs):
    global DEBUG
    if DEBUG:
        print(*args, **kwargs)


def print_progress(i, time_elapsed = None, before = "progress:", after = ""):
    """show progress of process, often used in training a neural network model
    params
        i: progress value in [0, 1.], double
        time_elapsed: time elapsed from progress 0.0 to current progress, double
        before: descriptive content displayed before progress i, str
        after: descriptive content displayed after progress i, str
    """
    if time_elapsed is not None:
        if i >= 1:
            time_remaining = 0
        elif 0 < i < 1:
            time_remaining = time_elapsed * (1. - i) / i
        else:
            time_remaining = float('inf')

    progress_info = '{:>7.2%}'.format(i) # align right, 7 characters atmost
    if time_elapsed is not None:
        progress_info += ' {:.0f}m{:.0f}s'.format(
            time_elapsed // 60, time_elapsed % 60)
        if 0 < i < 1.0:
            progress_info += ' {:.0f}m{:.0f}s'.format(
                time_remaining // 60, time_remaining % 60)

    # display progress repeatedly in the same line.
    progress_info = '\r' + before + progress_info + after
    sys.stdout.flush()
    sys.stdout.write(progress_info)
```

In [0]:

```
# build two directories for saving model and submission files.
folders = ['./models', './submissions']
for i in range(len(folders)):
    if not os.path.exists(folders[i]):
        debug("creat")
        try:
            debug("creating folder: '{}'. ".format(folders[i]), end = "")
            os.mkdir(folders[i])
            debug("success.")
        except():
            debug("failure.")
```

1.3 loading training data

In [0]:

```
data = np.loadtxt("PATCH.amat")
```

In [8]:

```
data.shape
```

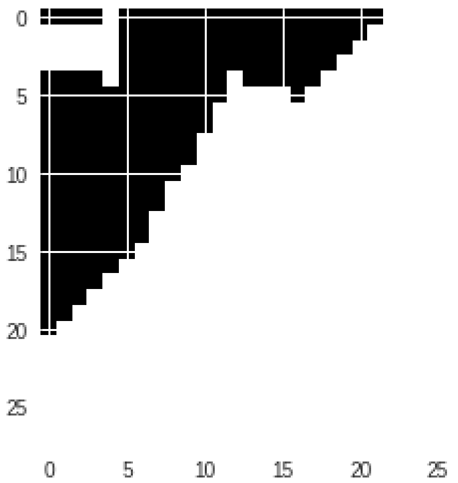
Out[8]:

```
(50000, 785)
```

We randomly display one example in the training dataset

In [9]:

```
id = random.randint(0, data.shape[0])
img = data[id,0:-1].reshape(28,28)
plt.imshow(img, cmap='gray')
plt.show()
print("class:",data[id,-1])
```




```
class: 0.0
```

In [0]:

```
X, y = data[:,:-1], data[:,-1]
```

1.4 Building Models

We build a simple residual convolutional neural network `Net5` using pytorch.

In [0]:

```
class MyModule(nn.Module):
    def __init__(self, p_fc, p_conv, suffix):
        super(MyModule, self).__init__()
        self.dropout_p = p_fc
        self.dropout_conv_p = p_conv
        self.suffix = suffix

    def get_name(self, suffix = None):
        if suffix is not None:
            self.suffix = suffix
        name =  type(self).__name__ +  "_" + str(self.dropout_p)
        name += "_" + str(self.dropout_conv_p) + "_" + str(suffix)
        return name

class Net5(MyModule):
    """CNN with best result"""
    def __init__(self, channels = [32, 64, 128, 128, 128],
                 p_fc = 0.0, p_conv = 0.0, hidden = 1000, suffix = ""):
        super(Net5, self).__init__(p_fc, p_conv, suffix)
        self.maxpool = nn.MaxPool2d(2, 2)
        self.conv1 = nn.Conv2d(1, channels[0], 3, stride = 1, padding = 1)
        self.conv1_bn = nn.BatchNorm2d(channels[0])
        self.conv2 = nn.Conv2d(channels[0], channels[1], 3, stride = 1,
                               padding = 1)
        self.conv2_bn = nn.BatchNorm2d(channels[1])

        self.conv3 = nn.Conv2d(channels[1], channels[2], 3, padding = 1)
        self.conv3_bn = nn.BatchNorm2d(channels[2])
        self.conv4 = nn.Conv2d(channels[2], channels[3], 3)
        self.conv4_bn = nn.BatchNorm2d(channels[3])
        self.conv5 = nn.Conv2d(channels[3], channels[4], 3)
        self.conv5_bn = nn.BatchNorm2d(channels[4])

        self.relu = nn.ReLU(inplace = True)
        self.fc1 = nn.Linear(channels[4]*4*4, hidden)
        self.fc_drop = nn.Dropout(p = self.dropout_p)
        self.fc2 = nn.Linear(hidden, n_class)


    def forward(self, x):                              # 1     28    28
        shortcut = x
        x = self.conv1_bn(self.relu(self.conv1(x)))    #31     28    28
        x = self.conv2_bn(self.relu(self.conv2(x)))    #64     28    28

        x += shortcut                                  #shortcut

        x = self.conv3_bn(self.relu(self.conv3(x)))    #128    28    28
        x = self.maxpool(x)                            #128    14    14

        x = self.conv4_bn(self.relu(self.conv4(x)))    #128    12    12
        x = self.maxpool(x)                            #128     6     6

        x = self.conv5_bn(self.relu(self.conv5(x)))    #128     4     4

        x = x.view(x.size(0), -1) # batch, 128
        x = self.fc_drop(x)
        x = self.fc1(x)
        x = self.fc2(x)
        return x
```

1.5 Training Model

Before training the model, we implemented a method to load batch data from the datasets.

In [12]:

```
def dataloader(phase, data_source,
               n_valid_sample = 1000,
               batch_size = 128,
               img_size = (30, 30)):
    """feed data to a training process with batch_size from a dataset
    params
        phase: decide whether the model is in 'train', 'val' or 'test'
        data_source: dataset np.array (sample_size, n_features)
        n_valid_sample: sample numbers for validating, int
        batch_size: int
        img_size: tuple, default (30, 30)
    return Iterable()
    """

    class Iterable(object):
        def __iter__(self):

            train_end = len(data_source) - n_valid_sample
            # use image size to compute number of features, some data_source may
            # not have the label(last column)
            n_feature = img_size[0] * img_size[1]

            if phase == 'train':
                data = data_source[ : train_end, :]
                #np.random.shuffle(data) # shuffle in subset
            elif phase == 'val':
                data = data_source[train_end : , :]
            else: # test dataset, no label column
                data = data_source

            inputs = data[:,:n_feature]
            if phase in ['train', 'val']: # have labels
                labels = data[:, -1]

            sample_size = inputs.shape[0]
            batches = int(np.ceil(sample_size / batch_size))
            #debug(batches)
            for j in range(batches):
                #debug("{} in dataloader".format(j))
                b_start = j * batch_size
                b_end = min(sample_size, (j + 1) * batch_size)

                batch_inputs = inputs[b_start:b_end, :]
                batch_inputs = torch.from_numpy(batch_inputs)
                batch_inputs = torch.unsqueeze(batch_inputs.view(
                    b_end-b_start, img_size[0], img_size[1]), dim = 1)

                if phase in ['train', 'val']:
                    batch_labels = labels[b_start:b_end]
                    batch_labels = torch.from_numpy(batch_labels)
                    batch_labels = batch_labels.type(torch.LongTensor)
                    yield batch_inputs, batch_labels
                else:
                    yield batch_inputs
    return Iterable()

debug(dataloader)
```

```
<function dataloader at 0x7f9832c76158>
```

We implemented a method `show_learning_curve` to plot the learning curve after training is finished.

In [0]:

```
def show_learning_curve(losses, accuracies):
    support = np.arange(len(losses['train']))
    plt.figure(figsize = (14, 6))
    plt.grid(True) # add a grid

    plt.subplot(1,2,1)
    plt.plot(support, losses['train'], 'g-', label = 'train')
    plt.plot(support, losses['val'], 'b-', label = 'val')
    plt.xlabel('epochs')
    plt.ylabel('losses')
    plt.title("Loss curves")
    plt.legend(loc='upper right')

    plt.subplot(1,2,2)
    plt.plot(support, accuracies['train'], 'g-', label = 'train' )
    plt.plot(support, accuracies['val'], 'b-', label = 'val')
    plt.xlabel('epochs')
    plt.ylabel('accuracy')
    plt.title("Accuracy curves")
    plt.legend(loc='lower right')
    plt.show()
```

The following method `train_model` is the core method where forward propagation, backward propagation, and parameters update is performed. It receives several parameters to control the training procedure.

In [14]:

```
def train_model(model,
                train_valid_set,
                criterion,
                optimizer,
                n_valid_sample,
                scheduler = None,
                auto_save_path = './models/auto_save.model',
                best_model_path = './models/best_model_',
                max_epochs = 20,
                early_stopping = False,
                epoch_patience = 5,
                auto_load_best_after_train = True,
                auto_save_interval = 1,
                batch_size = 128,
                show_live_progress = False
                ):
    """train a model
    params
        model: to be trained, nn.Module
        train_valid_set: merge of training and validating set
        optimizer: optimizer
        n_valid_sample: number of validating samples
        scheduler: learning rate scheduler
        auto_save_path: path where latest model will be auto saved
        best_model_path: path where best model will be saved
        max_epochs: max epochs, int
        early_stopping: if trainint will stop earlier, according to accuracy on
            validating dataset, Bool
        epoch_patience: if accuracy on validate set decreases, we don't stop
            at the epoch, we need to go extra epoch_patience number of epoch
            to confirm this decreasing trends, int
        auto_load_best_after_train: whether we load our best model paramters
            after the training process is complete, Bool
        auto_save_interval: the interval we auto save the parameters of the
            model, int
        batch_size: batch_size, int
    returns
        model: trained, nn.Module
        losses: losses during training and validating,
            dict {"train", [double], 'val': [double]}
        accuracies: accuracies during training and validating,
            dict {"train", [double], 'val': [double]}
        cache: a cache dict {'best_model_wts':best_model_wts,
                             'best_acc_val':best_acc_val,
                             'optimizer':optimizer,
                             'model':model
                            }
    """
    if train_valid_set is None:    # no data to train
        return model

    start = time.time()
    dataset_sizes = {
        'train': len(train_valid_set) - n_valid_sample,
        'val': n_valid_sample
    }

    dataloaders = {
        'train':dataloader('train',
```

```
                            data_source = train_valid_set,
                            n_valid_sample = n_valid_sample,
                            batch_size = batch_size,
                            img_size = NEW_IMG_SIZE),
        'val':dataloader('val',
                          data_source = train_valid_set,
                          n_valid_sample = n_valid_sample,
                          batch_size = batch_size,
                          img_size = NEW_IMG_SIZE)
    }

    best_model_wts = copy.deepcopy(model.state_dict())  # for best parameters
    best_acc = {'train':0.0, 'val':0.0}                 # best accuracy

    losses = {'train': [], 'val':[]}
    accuracies = {'train': [], 'val':[]}
    patience_used = 0                                   # patience used
    early_stopped = 0
    debug("'s': auto saved, '*': best accuracy so far.")

    for epoch in range(max_epochs):
        since = time.time()

        # s_before and s_after are for print trainig progress
        s_before = '[Epoch{:>3d}/{} '.format(epoch, max_epochs - 1)
        s_after = ']'
        if show_live_progress:
            print_progress(0, 0, s_before, s_after)
        else:
            print(s_before + s_after, end = "")

        # Each epoch has a training and validation phase
        for phase in ['train', 'val']:
            since_phase = time.time()
            if phase == 'train':
                if scheduler is not None:
                    scheduler.step()
                model.train()  # Set model to training mode
            else:
                model.eval()   # Set model to evaluate mode

            running_loss = 0.0
            running_corrects = 0
            running_size = 0
            if show_live_progress:
                print_progress(0, 0, s_before, s_after)

            # Iterate over data.
            for inputs, labels in dataloaders[phase]:
                inputs = inputs.to(device)
                labels = labels.to(device)
                # zero the parameter gradients
                optimizer.zero_grad()
                # forward
                # track history if only in train
                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, dim = 1)
                    loss = criterion(outputs, labels)

                    # backward + optimize only if in training phase
```

```
                if phase == 'train':
                    loss.backward()
                    optimizer.step()

            # accumulate loss and correctly predicted sample number
            running_loss += loss.item() * inputs.size(0)
            running_corrects += torch.sum(preds.data == labels.data).item()
            running_size += preds.size(0)

            if show_live_progress:
                time_elapsed = time.time() - since_phase
                print_progress(running_size/dataset_sizes[phase],
                               time_elapsed,
                               s_before,
                               s_after)
                already_show_estimated_time = True
            # end batches loop

        # compute average loss and accuracy after a traing or validate phase
        epoch_loss = running_loss / dataset_sizes[phase]
        epoch_acc = running_corrects / dataset_sizes[phase]

        # keep current loss and accuracy data
        losses[phase].append(epoch_loss)
        accuracies[phase].append(epoch_acc)

        time_elapsed = time.time() - since_phase
        s_after += ' {} loss: {:.4f} acc: {:<7.2%} '.format(
            phase, epoch_loss, epoch_acc)


        # check current parameters achieved best performance so far
        # if YES, keep a reference to the best parameters.
        if epoch_acc > best_acc[phase]:
            best_acc[phase] = epoch_acc
            if phase == 'val':
                s_after += " *"
                best_model_wts = copy.deepcopy(model.state_dict())
                patience_used = 0
        else:
            if phase == 'val': # avoid repeating check for both training
                               # and validating phase
                patience_used += 1 #
                if early_stopping and patience_used >= epoch_patience:
                    # patience is used up
                    early_stopped = epoch - epoch_patience + 1

        if show_live_progress:
            print_progress(running_size/dataset_sizes[phase],
                           time_elapsed, s_before, s_after)
        else:
            print(' {} loss: {:.4f} acc: {:<7.2%} '.format(
                phase, epoch_loss, epoch_acc), end = " ")

        #end phase loop

    time_elapsed = time.time() - since
    if show_live_progress:
        print_progress(1, time_elapsed, s_before, s_after)
    else:
        print(' {:.0f}m{:.0f}s'.format(
```

```
                time_elapsed // 60, time_elapsed % 60), end = "")
        # display some information
        #if epoch_acc == best_acc['val']:
        #    print("*", end="")
        #else:
        #    print("", end="")
        if early_stopped or epoch == (max_epochs - 1) or \
           (epoch + 1) % auto_save_interval == 0:

            torch.save(model.state_dict(), auto_save_path)
            torch.save(best_model_wts, best_model_path)
            print(" s") # saved
        else:
            print("") # new line

        if early_stopped > 0:
            print("Early stop at epoch: {}".format(early_stopped))
            break
        #end epoch loop


    time_elapsed = time.time() - start
    print('Training complete in {:.0f}m {:.0f}s'.format(
            time_elapsed // 60, time_elapsed % 60))

    print('Best val Acc on val:   {:.2%}'.format(best_acc['val']))
    print('Best val Acc on train: {:.2%}'.format(best_acc['train']))
    # load best model weights

    if auto_load_best_after_train:
        model.load_state_dict(best_model_wts)

    train_info = {
        "best_acc_train": best_acc["train"],
        "best_acc_val": best_acc["val"],
        "time_elapsed": time_elapsed,
        "early_stopped": early_stopped,
        "epoch_passed": epoch + 1
    }
    return model, losses, accuracies, train_info

debug(train_model)
```

```
<function train_model at 0x7f987a5f8f28>
```

In the following cell, we create some instances of `Net5` , set the training control parameters, split training dataset to training and validating dataset, and train the models. We will train 12 `Net5` models. All trained models will be saved to 2 files: one stores the latest parameters, and the other stores the parameters with which the model performs best on validating dataset.

In [15]:

```
n_class = 2
NEW_IMG_SIZE = (28, 28)

models = []
for i in range(15):
    models.append(Net5(p_fc = 0.5, channels = [32, 64, 128, 128, 128]))

caches = []

train_config = {
    "n_min_valid_set": 128,
    "n_test_set": 5000,
    "shuffle_before_split": True,
    "use_norm": True, # use_normalization,
    "batch_size": 128,
    "trainer": "YQ",
    "max_epochs": 30,
    "early_stopping": True,
    "epoch_patience": 5,
    "auto_load_best_after_train": True,
    "auto_save_interval": 5,
    "show_live_progress": True
}

debug("global training configuration: ")
for item in train_config.items():
    debug(item)


# apply different train / val split for different models
n_valid_sample = [5000] * len(models)
# or set different number of validate set like:
# n_valid_sample = [1500, 1000, 500, 2000, 1500... ]
#[15000, 500, 500, 500, 500, 1000, 1000, 1000, 1000, 1000]
# minimal smple number for validating

# all training samples are in total_set
total_set = data
#total_set = np.concatenate((X_resized, image_labels.reshape(-1, 1)), axis = 1)

if train_config["shuffle_before_split"]:
    np.random.shuffle(total_set) # not need this?

# split the total dataset to train_valid and test set.
n_total_set = total_set.shape[0]
test_start = n_total_set - train_config["n_test_set"]

# load pre-processed train data as a whole train_valid_test set.
debug("reserve {} samples for testing".format(train_config["n_test_set"]))
train_valid_set = total_set[:n_total_set - train_config["n_test_set"],:]
test_set = None
if train_config["n_test_set"] > 0:
    test_set = total_set[n_total_set - train_config["n_test_set"]:,:]

# training each model
for i, model in enumerate(models):

    debug("\n================== model{}: {} ================== ".format(
        i, type(model).__name__))
```

```
    hp_params = {
        "model_name": type(model).__name__,
        "lr": 1e-3,
        "weight_decay": 0,
        "n_test_set": train_config["n_test_set"],
        "dropout_p": model.dropout_p,
        "dropout_conv_p": model.dropout_conv_p,
    }

    # loss function
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr = hp_params["lr"],
                           weight_decay = hp_params["weight_decay"])
    #scheduler = lr_scheduler.StepLR(optimizer,
    #                                step_size = 5,
    #                                gamma = 0.5)

    # optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
    # Decay lr: first 10 epochs: 1e-3, last 10 epochs 1e-5, in middle: 1e-4
    scheduler = lr_scheduler.MultiStepLR(
        optimizer,
        milestones = [5,10,15,train_config["max_epochs"]-5],
        gamma = 0.1)

    suffix = "_" + train_config["trainer"] + "_" + str(i)
    debug('training model: {}, lr: {}, weight_decay:{}'.format(
        model.get_name(suffix),
        optimizer.param_groups[0]['lr'],
        optimizer.param_groups[0]['weight_decay']))

    if train_config["shuffle_before_split"]:
        debug("shuffling train_valid_set before splitting... ", end = "")
        np.random.shuffle(train_valid_set)
        debug("complete.")

    # reload train_valid_set from total_set
    train_valid_set = total_set[:n_total_set - train_config["n_test_set"],:]

    # split dataset to train / valid sets
    n_train_valid_set = train_valid_set.shape[0]
    cur_valid_sample = max(n_valid_sample[i], train_config["n_min_valid_set"])
    hp_params["n_valid_set"] = cur_valid_sample

    train_set = train_valid_set[0: -cur_valid_sample,:]
    valid_set = train_valid_set[-cur_valid_sample: ,:]

    debug("split train_valid_set to {} / {} samples".format(
        n_train_valid_set - cur_valid_sample, cur_valid_sample))

    #view_data_distribution(valid_set[:,-1], "valid_set", int_to_label)


    # data augmentation on training set
    n_train_set = train_set.shape[0]
    hp_params["n_train_set"] = n_train_set

    np.random.shuffle(train_set)
    #view_data_distribution(train_set[:,-1], "train_set", int_to_label)

    # build new train_valid_set by merging train set with valid set
```

```
    train_valid_set = np.concatenate((train_set, valid_set), axis = 0)

    # set model save path
    best_model_path = './models/best_model_' + model.get_name(suffix)
    auto_save_path = './models/auto_save_' + model.get_name(suffix)

    # pre-trained model from file
    # careful: this may cause model saw samples in validating set.
    # must NOT use pre-trained model if whole train / valid set si shuffled
    #model = load_model(model, best_model_path, auto_save_path)

    model.to(device)
    model.train()

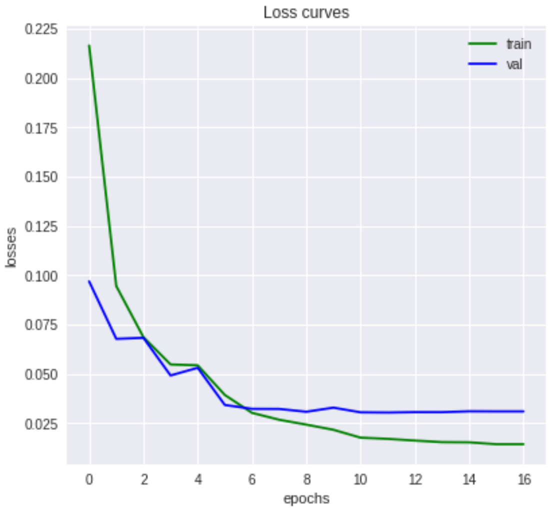
    debug("train_set size:{}, valid_set size:{}".format(
        hp_params["n_train_set"], hp_params["n_valid_set"]))

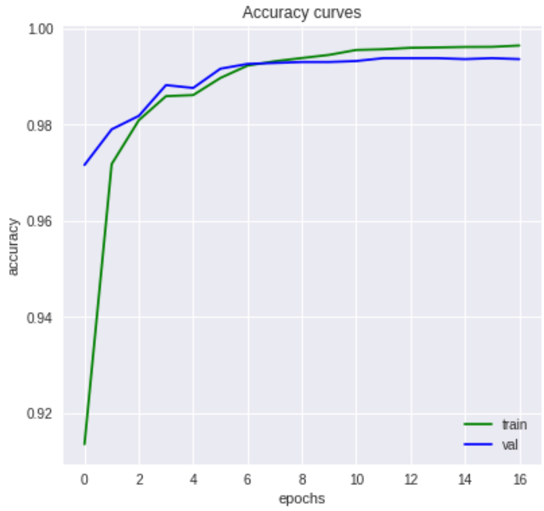
    # perform training process
    model, loss, accuracies, train_result = train_model(
        model,
        train_valid_set,
        criterion,
        optimizer,
        n_valid_sample = cur_valid_sample,
        scheduler = scheduler,
        max_epochs = train_config["max_epochs"],
        early_stopping = train_config["early_stopping"],
        epoch_patience = train_config["epoch_patience"],
        auto_load_best_after_train = train_config["auto_load_best_after_train"],
        auto_save_path = auto_save_path,
        best_model_path = best_model_path,
        auto_save_interval = train_config["auto_save_interval"],
        batch_size = train_config["batch_size"],
        show_live_progress = train_config["show_live_progress"]
    )
    caches.append(train_result)

    show_learning_curve(loss, accuracies)
    for item in train_config.items():
        debug(item)
    for item in train_result.items():
        debug(item)
```

```
global training configuration:
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
reserve 5000 samples for testing

================== model0: Net5 ==================
training model: Net5_0.5_0.0__YQ_0, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m49s] train loss: 0.2164 acc: 91.36%   val lo
ss: 0.0968 acc: 97.16%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.0945 acc: 97.18%   val lo
ss: 0.0677 acc: 97.90%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0686 acc: 98.09%   val lo
ss: 0.0682 acc: 98.18%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0547 acc: 98.59%   val lo
ss: 0.0491 acc: 98.82%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0543 acc: 98.61%   val lo
ss: 0.0530 acc: 98.76%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0393 acc: 98.97%   val lo
ss: 0.0342 acc: 99.16%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0302 acc: 99.22%   val lo
ss: 0.0322 acc: 99.26%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0267 acc: 99.31%   val lo
ss: 0.0322 acc: 99.28%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0242 acc: 99.38%   val lo
ss: 0.0307 acc: 99.30%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0216 acc: 99.45%   val lo
ss: 0.0328 acc: 99.30%   s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0176 acc: 99.55%   val lo
ss: 0.0305 acc: 99.32%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0170 acc: 99.56%   val lo
ss: 0.0303 acc: 99.38%   *
[Epoch 12/29 100.00% 0m49s] train loss: 0.0161 acc: 99.59%   val lo
ss: 0.0305 acc: 99.38%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0153 acc: 99.60%   val lo
ss: 0.0305 acc: 99.38%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0152 acc: 99.61%   val lo
ss: 0.0310 acc: 99.36%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0143 acc: 99.61%   val lo
ss: 0.0309 acc: 99.38%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0143 acc: 99.64%   val lo
ss: 0.0309 acc: 99.36%   s
Early stop at epoch: 12
Training complete in 13m 58s
Best val Acc on val:   99.38%
Best val Acc on train: 99.64%
```

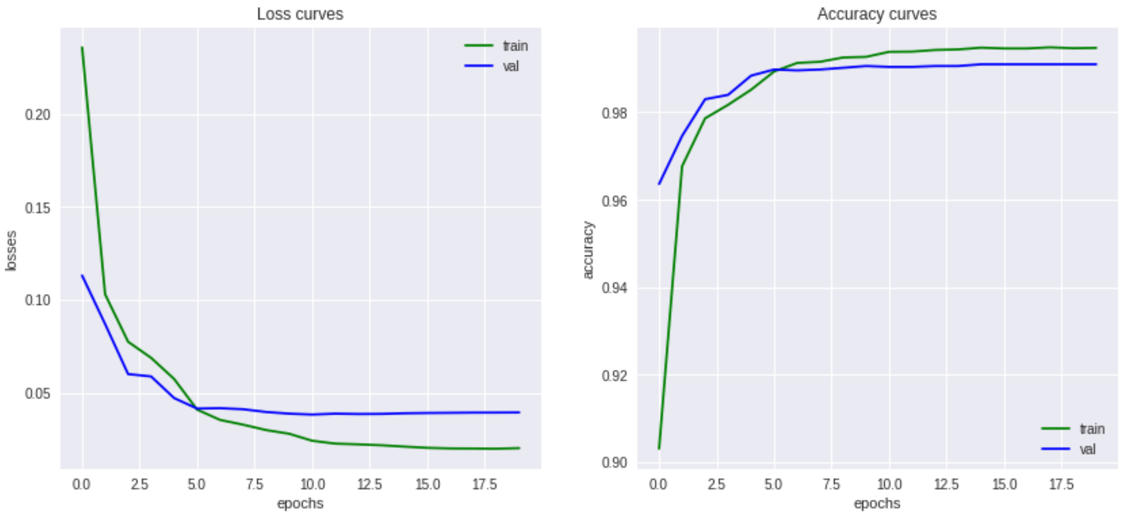

Loss curves
losses
epochs
train
val
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0 2 4 6 8 10 12 14 16


Accuracy curves
accuracy
epochs
train
val
1.00
0.98
0.96
0.94
0.92
0 2 4 6 8 10 12 14 16

```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.996425)
('best_acc_val', 0.9938)
('time_elapsed', 838.4093170166016)
('early_stopped', 12)
('epoch_passed', 17)

================== model1: Net5 ==================
training model: Net5_0.5_0.0__YQ_1, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2357 acc: 90.30%   val lo
ss: 0.1130 acc: 96.36%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.1029 acc: 96.77%   val lo
ss: 0.0869 acc: 97.46%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0774 acc: 97.86%   val lo
ss: 0.0600 acc: 98.30%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0687 acc: 98.17%   val lo
ss: 0.0587 acc: 98.40%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0573 acc: 98.52%   val lo
ss: 0.0471 acc: 98.84%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0408 acc: 98.94%   val lo
ss: 0.0414 acc: 98.98%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0353 acc: 99.13%   val lo
ss: 0.0416 acc: 98.96%
[Epoch  7/29 100.00% 0m49s] train loss: 0.0327 acc: 99.16%   val lo
ss: 0.0411 acc: 98.98%
[Epoch  8/29 100.00% 0m49s] train loss: 0.0298 acc: 99.26%   val lo
ss: 0.0396 acc: 99.02%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0279 acc: 99.27%   val lo
ss: 0.0387 acc: 99.06%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0241 acc: 99.39%   val lo
ss: 0.0382 acc: 99.04%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0226 acc: 99.39%   val lo
ss: 0.0387 acc: 99.04%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0222 acc: 99.43%   val lo
ss: 0.0385 acc: 99.06%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0217 acc: 99.44%   val lo
ss: 0.0385 acc: 99.06%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0210 acc: 99.48%   val lo
ss: 0.0389 acc: 99.10%   * s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0203 acc: 99.46%   val lo
ss: 0.0390 acc: 99.10%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0200 acc: 99.46%   val lo
ss: 0.0391 acc: 99.10%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0199 acc: 99.49%   val lo
ss: 0.0392 acc: 99.10%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0198 acc: 99.47%   val lo
```

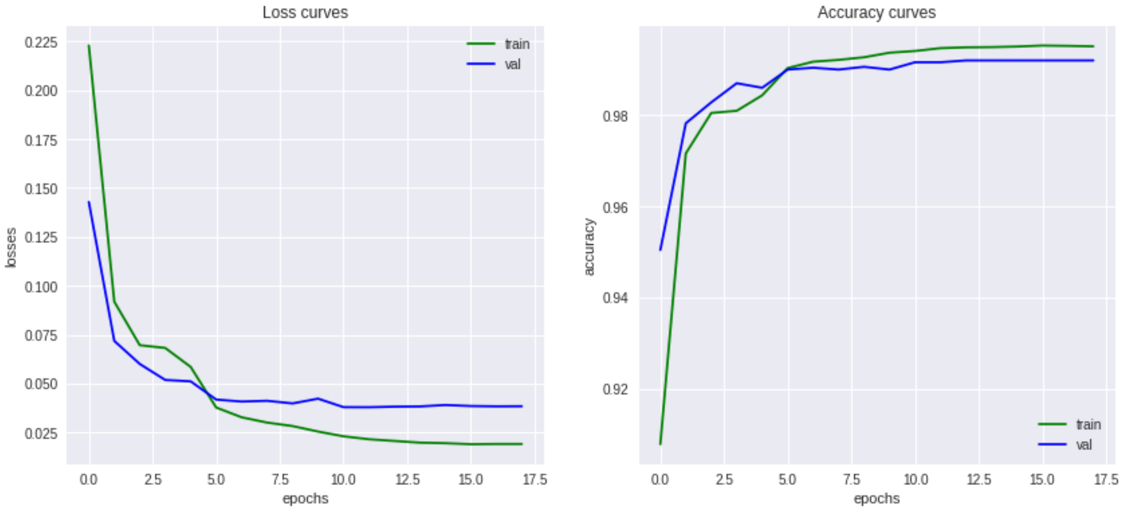
```
ss: 0.0393 acc: 99.10%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0201 acc: 99.48%   val lo
ss: 0.0393 acc: 99.10%   s
Early stop at epoch: 15
Training complete in 16m 27s
Best val Acc on val:   99.10%
Best val Acc on train: 99.49%
```



```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.994875)
('best_acc_val', 0.991)
('time_elapsed', 986.5288460254669)
('early_stopped', 15)
('epoch_passed', 20)

================== model2: Net5 ==================
training model: Net5_0.5_0.0__YQ_2, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2229 acc: 90.78%   val lo
ss: 0.1429 acc: 95.04%   *
[Epoch  1/29 100.00% 0m50s] train loss: 0.0919 acc: 97.16%   val lo
ss: 0.0718 acc: 97.82%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0696 acc: 98.05%   val lo
ss: 0.0600 acc: 98.28%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0682 acc: 98.09%   val lo
ss: 0.0518 acc: 98.70%   *
[Epoch  4/29 100.00% 0m50s] train loss: 0.0585 acc: 98.43%   val lo
ss: 0.0511 acc: 98.60%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0378 acc: 99.03%   val lo
ss: 0.0418 acc: 99.00%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0328 acc: 99.17%   val lo
ss: 0.0408 acc: 99.04%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0301 acc: 99.21%   val lo
ss: 0.0412 acc: 99.00%
[Epoch  8/29 100.00% 0m49s] train loss: 0.0283 acc: 99.27%   val lo
ss: 0.0398 acc: 99.06%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0255 acc: 99.37%   val lo
ss: 0.0423 acc: 99.00%   s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0230 acc: 99.41%   val lo
ss: 0.0379 acc: 99.16%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0215 acc: 99.47%   val lo
ss: 0.0379 acc: 99.16%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0207 acc: 99.49%   val lo
ss: 0.0382 acc: 99.20%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0198 acc: 99.49%   val lo
ss: 0.0383 acc: 99.20%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0195 acc: 99.50%   val lo
ss: 0.0390 acc: 99.20%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0190 acc: 99.53%   val lo
ss: 0.0385 acc: 99.20%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0191 acc: 99.52%   val lo
ss: 0.0383 acc: 99.20%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0191 acc: 99.51%   val lo
ss: 0.0384 acc: 99.20%   s
Early stop at epoch: 13
```

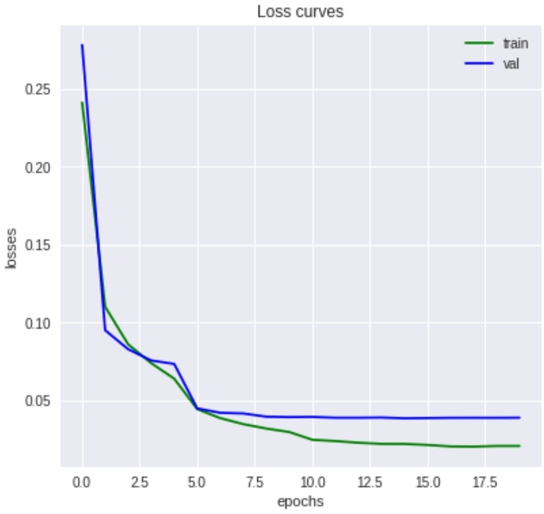
```
Training complete in 14m 51s
Best val Acc on val:   99.20%
Best val Acc on train: 99.53%
```

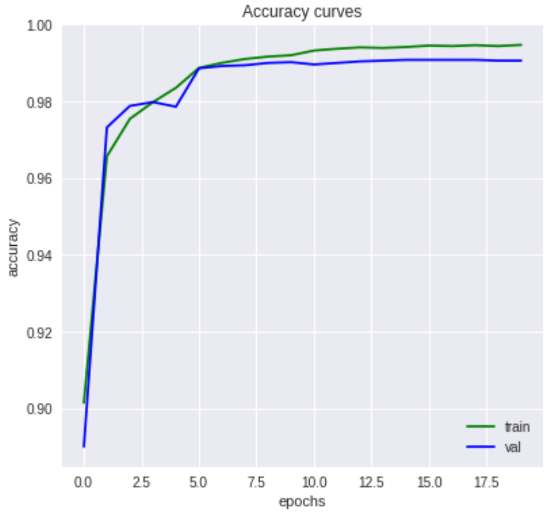


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995275)
('best_acc_val', 0.992)
('time_elapsed', 890.9551587104797)
('early_stopped', 13)
('epoch_passed', 18)

================== model3: Net5 ==================
training model: Net5_0.5_0.0__YQ_3, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2409 acc: 90.14%   val lo
ss: 0.2778 acc: 89.00%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.1100 acc: 96.57%   val lo
ss: 0.0950 acc: 97.32%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0859 acc: 97.54%   val lo
ss: 0.0828 acc: 97.88%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0739 acc: 97.98%   val lo
ss: 0.0756 acc: 97.98%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0639 acc: 98.35%   val lo
ss: 0.0733 acc: 97.86%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0444 acc: 98.87%   val lo
ss: 0.0448 acc: 98.86%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0386 acc: 99.00%   val lo
ss: 0.0420 acc: 98.92%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0348 acc: 99.10%   val lo
ss: 0.0416 acc: 98.94%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0319 acc: 99.17%   val lo
ss: 0.0395 acc: 99.00%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0297 acc: 99.20%   val lo
ss: 0.0393 acc: 99.02%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0247 acc: 99.32%   val lo
ss: 0.0394 acc: 98.96%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0239 acc: 99.37%   val lo
ss: 0.0389 acc: 99.00%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0228 acc: 99.41%   val lo
ss: 0.0389 acc: 99.04%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0221 acc: 99.39%   val lo
ss: 0.0390 acc: 99.06%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0221 acc: 99.41%   val lo
ss: 0.0385 acc: 99.08%   * s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0214 acc: 99.45%   val lo
ss: 0.0387 acc: 99.08%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0205 acc: 99.44%   val lo
ss: 0.0388 acc: 99.08%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0203 acc: 99.46%   val lo
ss: 0.0388 acc: 99.08%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0208 acc: 99.44%   val lo
```

```
ss: 0.0388 acc: 99.06%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0208 acc: 99.47%   val lo
ss: 0.0389 acc: 99.06%   s
Early stop at epoch: 15
Training complete in 16m 26s
Best val Acc on val:   99.08%
Best val Acc on train: 99.47%
```

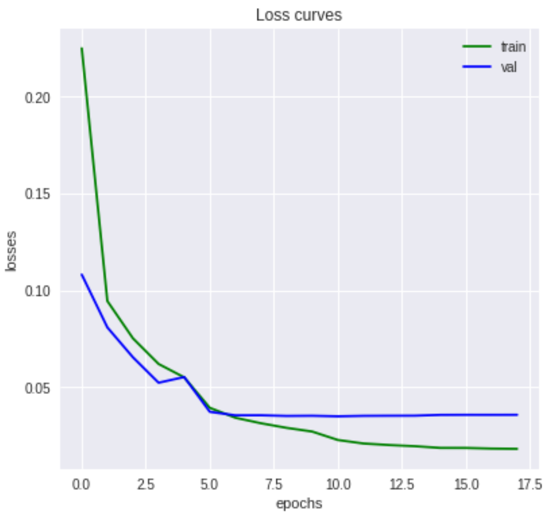


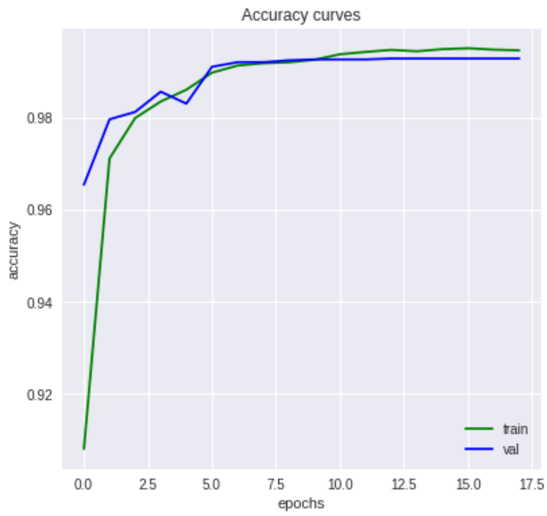


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.9947)
('best_acc_val', 0.9908)
('time_elapsed', 985.8478403091431)
('early_stopped', 15)
('epoch_passed', 20)

================== model4: Net5 ==================
training model: Net5_0.5_0.0__YQ_4, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2249 acc: 90.81%   val lo
ss: 0.1081 acc: 96.54%   *
[Epoch  1/29 100.00% 0m50s] train loss: 0.0944 acc: 97.11%   val lo
ss: 0.0808 acc: 97.96%   *
[Epoch  2/29 100.00% 0m50s] train loss: 0.0751 acc: 97.99%   val lo
ss: 0.0654 acc: 98.12%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0619 acc: 98.35%   val lo
ss: 0.0522 acc: 98.56%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0550 acc: 98.60%   val lo
ss: 0.0552 acc: 98.30%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0393 acc: 98.97%   val lo
ss: 0.0372 acc: 99.10%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0342 acc: 99.13%   val lo
ss: 0.0354 acc: 99.20%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0313 acc: 99.18%   val lo
ss: 0.0355 acc: 99.20%
[Epoch  8/29 100.00% 0m49s] train loss: 0.0290 acc: 99.20%   val lo
ss: 0.0351 acc: 99.24%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0270 acc: 99.25%   val lo
ss: 0.0352 acc: 99.26%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0227 acc: 99.37%   val lo
ss: 0.0349 acc: 99.26%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0209 acc: 99.42%   val lo
ss: 0.0352 acc: 99.26%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0201 acc: 99.47%   val lo
ss: 0.0352 acc: 99.28%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0195 acc: 99.44%   val lo
ss: 0.0353 acc: 99.28%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0186 acc: 99.48%   val lo
ss: 0.0357 acc: 99.28%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0186 acc: 99.50%   val lo
ss: 0.0357 acc: 99.28%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0183 acc: 99.47%   val lo
ss: 0.0357 acc: 99.28%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0181 acc: 99.46%   val lo
ss: 0.0357 acc: 99.28%   s
Early stop at epoch: 13
```

```
Training complete in 14m 51s
Best val Acc on val:   99.28%
Best val Acc on train: 99.50%
```

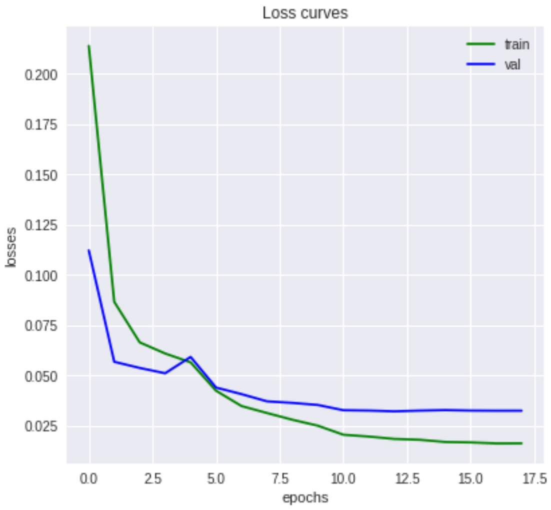


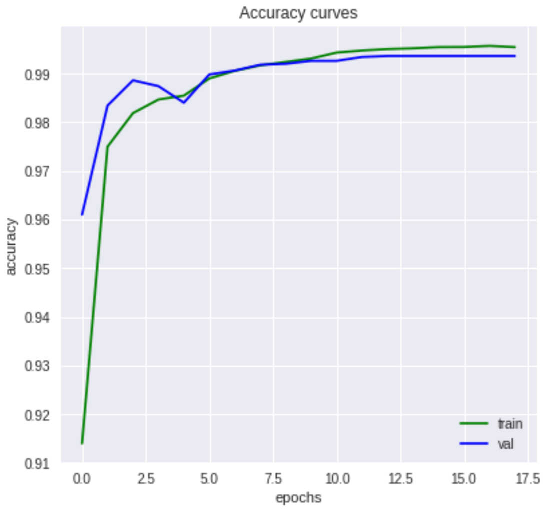


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995025)
('best_acc_val', 0.9928)
('time_elapsed', 890.7223167419434)
('early_stopped', 13)
('epoch_passed', 18)

================== model5: Net5 ==================
training model: Net5_0.5_0.0__YQ_5, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2139 acc: 91.40%   val lo
ss: 0.1121 acc: 96.10%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.0865 acc: 97.50%   val lo
ss: 0.0567 acc: 98.34%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0663 acc: 98.19%   val lo
ss: 0.0536 acc: 98.86%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0608 acc: 98.47%   val lo
ss: 0.0509 acc: 98.74%
[Epoch  4/29 100.00% 0m49s] train loss: 0.0564 acc: 98.55%   val lo
ss: 0.0591 acc: 98.40%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0422 acc: 98.90%   val lo
ss: 0.0438 acc: 98.98%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0346 acc: 99.06%   val lo
ss: 0.0406 acc: 99.06%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0312 acc: 99.17%   val lo
ss: 0.0370 acc: 99.18%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0278 acc: 99.24%   val lo
ss: 0.0362 acc: 99.20%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0248 acc: 99.31%   val lo
ss: 0.0352 acc: 99.26%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0203 acc: 99.43%   val lo
ss: 0.0325 acc: 99.26%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0194 acc: 99.47%   val lo
ss: 0.0324 acc: 99.34%   *
[Epoch 12/29 100.00% 0m49s] train loss: 0.0183 acc: 99.50%   val lo
ss: 0.0320 acc: 99.36%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0178 acc: 99.52%   val lo
ss: 0.0324 acc: 99.36%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0167 acc: 99.54%   val lo
ss: 0.0326 acc: 99.36%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0165 acc: 99.54%   val lo
ss: 0.0324 acc: 99.36%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0160 acc: 99.57%   val lo
ss: 0.0323 acc: 99.36%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0161 acc: 99.54%   val lo
ss: 0.0323 acc: 99.36%   s
Early stop at epoch: 13
```

```
Training complete in 14m 50s
Best val Acc on val:   99.36%
Best val Acc on train: 99.57%
```

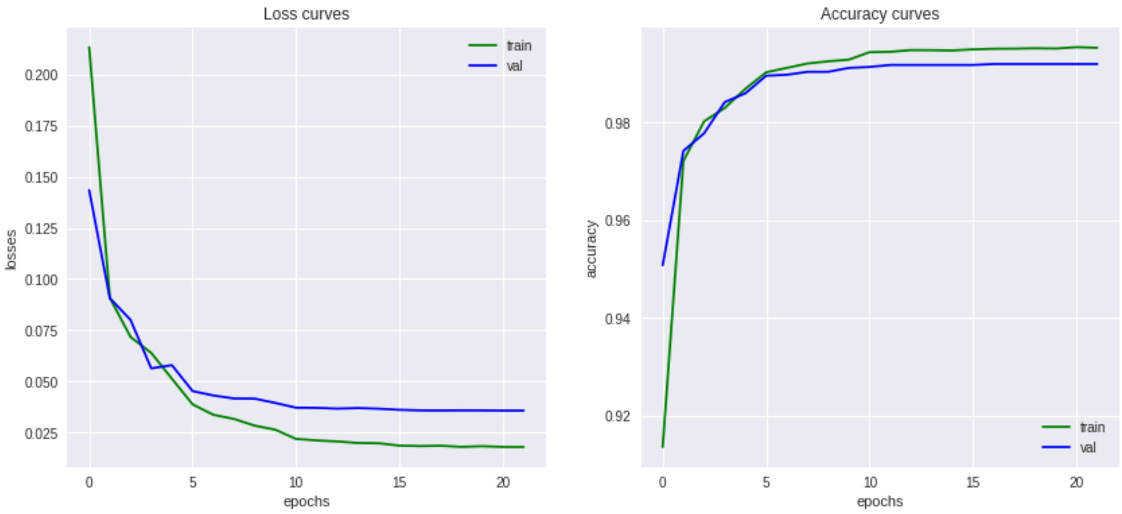




```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995675)
('best_acc_val', 0.9936)
('time_elapsed', 890.0589621067047)
('early_stopped', 13)
('epoch_passed', 18)

================== model6: Net5 ==================
training model: Net5_0.5_0.0__YQ_6, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2135 acc: 91.36%   val lo
ss: 0.1435 acc: 95.08%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.0908 acc: 97.21%   val lo
ss: 0.0906 acc: 97.42%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0716 acc: 98.02%   val lo
ss: 0.0800 acc: 97.78%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0638 acc: 98.30%   val lo
ss: 0.0563 acc: 98.42%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0512 acc: 98.69%   val lo
ss: 0.0579 acc: 98.60%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0387 acc: 99.03%   val lo
ss: 0.0452 acc: 98.96%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0336 acc: 99.12%   val lo
ss: 0.0430 acc: 98.98%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0315 acc: 99.21%   val lo
ss: 0.0415 acc: 99.04%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0283 acc: 99.26%   val lo
ss: 0.0415 acc: 99.04%
[Epoch  9/29 100.00% 0m49s] train loss: 0.0263 acc: 99.29%   val lo
ss: 0.0394 acc: 99.12%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0218 acc: 99.44%   val lo
ss: 0.0370 acc: 99.14%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0210 acc: 99.45%   val lo
ss: 0.0370 acc: 99.18%   *
[Epoch 12/29 100.00% 0m49s] train loss: 0.0205 acc: 99.48%   val lo
ss: 0.0366 acc: 99.18%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0198 acc: 99.48%   val lo
ss: 0.0369 acc: 99.18%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0196 acc: 99.48%   val lo
ss: 0.0365 acc: 99.18%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0185 acc: 99.50%   val lo
ss: 0.0360 acc: 99.18%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0183 acc: 99.51%   val lo
ss: 0.0357 acc: 99.20%   *
[Epoch 17/29 100.00% 0m49s] train loss: 0.0184 acc: 99.52%   val lo
ss: 0.0357 acc: 99.20%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0179 acc: 99.52%   val lo
```

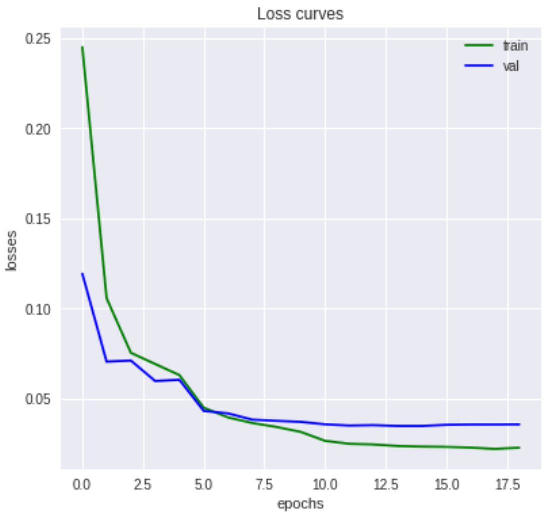
```
ss: 0.0357 acc: 99.20%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0182 acc: 99.52%   val lo
ss: 0.0357 acc: 99.20%   s
[Epoch 20/29 100.00% 0m49s] train loss: 0.0178 acc: 99.54%   val lo
ss: 0.0356 acc: 99.20%
[Epoch 21/29 100.00% 0m49s] train loss: 0.0178 acc: 99.53%   val lo
ss: 0.0356 acc: 99.20%   s
Early stop at epoch: 17
Training complete in 18m 5s
Best val Acc on val:   99.20%
Best val Acc on train: 99.54%
```

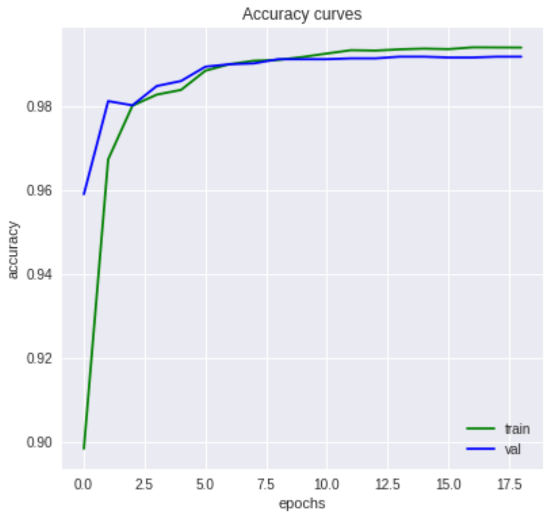


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.99545)
('best_acc_val', 0.992)
('time_elapsed', 1084.934482574463)
('early_stopped', 17)
('epoch_passed', 22)

================== model7: Net5 ==================
training model: Net5_0.5_0.0__YQ_7, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2448 acc: 89.83%   val lo
ss: 0.1191 acc: 95.90%   *
[Epoch  1/29 100.00% 0m50s] train loss: 0.1056 acc: 96.73%   val lo
ss: 0.0703 acc: 98.12%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0752 acc: 98.01%   val lo
ss: 0.0709 acc: 98.02%
[Epoch  3/29 100.00% 0m49s] train loss: 0.0690 acc: 98.28%   val lo
ss: 0.0596 acc: 98.48%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0629 acc: 98.39%   val lo
ss: 0.0602 acc: 98.60%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0448 acc: 98.84%   val lo
ss: 0.0430 acc: 98.94%   *
[Epoch  6/29 100.00% 0m50s] train loss: 0.0394 acc: 99.00%   val lo
ss: 0.0416 acc: 99.00%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0363 acc: 99.08%   val lo
ss: 0.0381 acc: 99.02%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0341 acc: 99.10%   val lo
ss: 0.0375 acc: 99.12%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0313 acc: 99.17%   val lo
ss: 0.0369 acc: 99.12%   s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0264 acc: 99.26%   val lo
ss: 0.0355 acc: 99.12%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0247 acc: 99.33%   val lo
ss: 0.0349 acc: 99.14%   *
[Epoch 12/29 100.00% 0m49s] train loss: 0.0244 acc: 99.33%   val lo
ss: 0.0351 acc: 99.14%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0235 acc: 99.36%   val lo
ss: 0.0346 acc: 99.18%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0232 acc: 99.37%   val lo
ss: 0.0346 acc: 99.18%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0230 acc: 99.36%   val lo
ss: 0.0353 acc: 99.16%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0226 acc: 99.40%   val lo
ss: 0.0354 acc: 99.16%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0219 acc: 99.40%   val lo
ss: 0.0354 acc: 99.18%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0226 acc: 99.40%   val lo
```

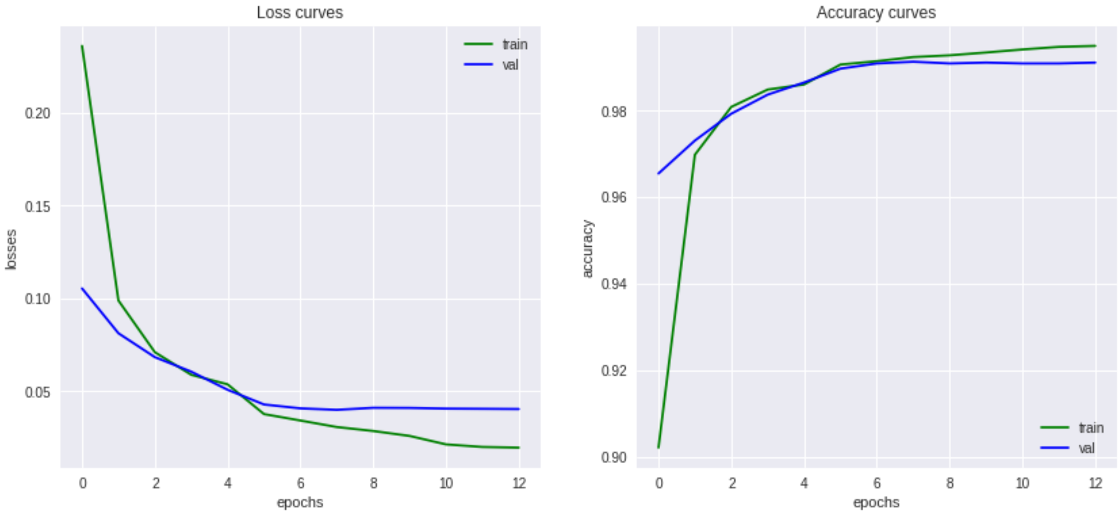
```
ss: 0.0355 acc: 99.18%   s
Early stop at epoch: 14
Training complete in 15m 40s
Best val Acc on val:   99.18%
Best val Acc on train: 99.40%
```





```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.994025)
('best_acc_val', 0.9918)
('time_elapsed', 940.0208373069763)
('early_stopped', 14)
('epoch_passed', 19)

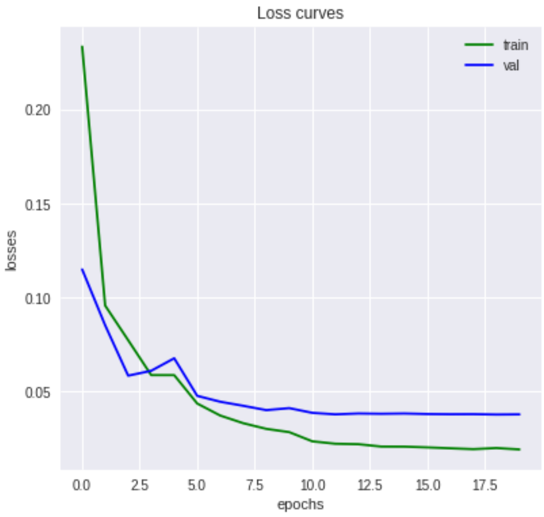
================== model8: Net5 ==================
training model: Net5_0.5_0.0__YQ_8, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2360 acc: 90.21%   val lo
ss: 0.1054 acc: 96.54%   *
[Epoch  1/29 100.00% 0m50s] train loss: 0.0989 acc: 96.97%   val lo
ss: 0.0812 acc: 97.30%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0711 acc: 98.08%   val lo
ss: 0.0684 acc: 97.92%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0589 acc: 98.48%   val lo
ss: 0.0606 acc: 98.36%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0537 acc: 98.59%   val lo
ss: 0.0508 acc: 98.64%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0377 acc: 99.06%   val lo
ss: 0.0429 acc: 98.96%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0342 acc: 99.13%   val lo
ss: 0.0408 acc: 99.08%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0307 acc: 99.23%   val lo
ss: 0.0400 acc: 99.12%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0286 acc: 99.27%   val lo
ss: 0.0411 acc: 99.08%
[Epoch  9/29 100.00% 0m49s] train loss: 0.0259 acc: 99.33%   val lo
ss: 0.0410 acc: 99.10%   s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0214 acc: 99.40%   val lo
ss: 0.0407 acc: 99.08%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0200 acc: 99.46%   val lo
ss: 0.0405 acc: 99.08%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0196 acc: 99.48%   val lo
ss: 0.0404 acc: 99.10%   s
Early stop at epoch: 8
Training complete in 10m 43s
Best val Acc on val:   99.12%
Best val Acc on train: 99.48%
```

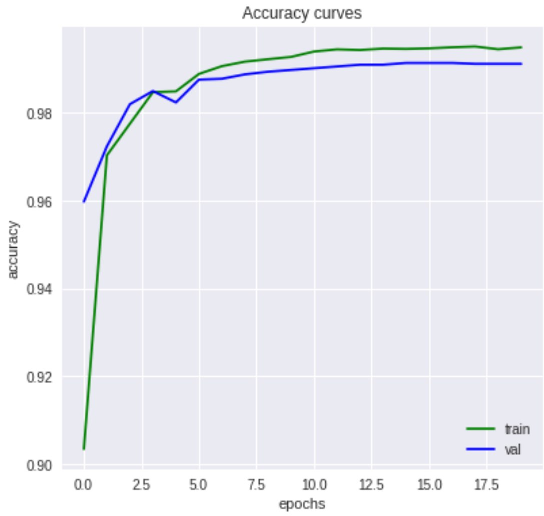

Loss curves
train
val
losses
0.20
0.15
0.10
0.05
0
2
4
6
8
10
12
epochs
Accuracy curves
accuracy
0.98
0.96
0.94
0.92
0.90
train
val
epochs

```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.99485)
('best_acc_val', 0.9912)
('time_elapsed', 642.8020238876343)
('early_stopped', 8)
('epoch_passed', 13)

================== model9: Net5 ==================
training model: Net5_0.5_0.0__YQ_9, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2336 acc: 90.34%   val lo
ss: 0.1149 acc: 95.98%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.0956 acc: 97.04%   val lo
ss: 0.0851 acc: 97.24%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0772 acc: 97.76%   val lo
ss: 0.0583 acc: 98.20%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0586 acc: 98.47%   val lo
ss: 0.0609 acc: 98.50%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0586 acc: 98.49%   val lo
ss: 0.0676 acc: 98.24%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0435 acc: 98.89%   val lo
ss: 0.0476 acc: 98.76%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0371 acc: 99.07%   val lo
ss: 0.0444 acc: 98.78%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0330 acc: 99.17%   val lo
ss: 0.0423 acc: 98.88%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0300 acc: 99.22%   val lo
ss: 0.0400 acc: 98.94%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0282 acc: 99.28%   val lo
ss: 0.0410 acc: 98.98%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0234 acc: 99.40%   val lo
ss: 0.0385 acc: 99.02%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0221 acc: 99.45%   val lo
ss: 0.0377 acc: 99.06%   *
[Epoch 12/29 100.00% 0m49s] train loss: 0.0218 acc: 99.44%   val lo
ss: 0.0382 acc: 99.10%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0206 acc: 99.47%   val lo
ss: 0.0380 acc: 99.10%
[Epoch 14/29 100.00% 0m49s] train loss: 0.0205 acc: 99.46%   val lo
ss: 0.0382 acc: 99.14%   * s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0201 acc: 99.47%   val lo
ss: 0.0379 acc: 99.14%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0197 acc: 99.50%   val lo
ss: 0.0378 acc: 99.14%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0192 acc: 99.52%   val lo
ss: 0.0378 acc: 99.12%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0198 acc: 99.45%   val lo
```

```
ss: 0.0376 acc: 99.12%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0190 acc: 99.50%   val lo
ss: 0.0377 acc: 99.12%   s
Early stop at epoch: 15
Training complete in 16m 27s
Best val Acc on val:   99.14%
Best val Acc on train: 99.52%
```

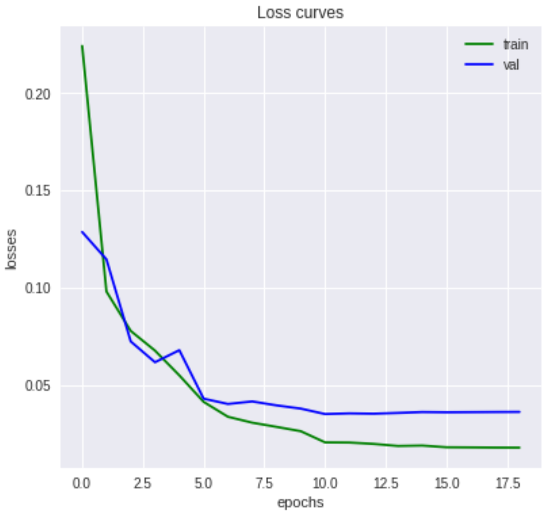


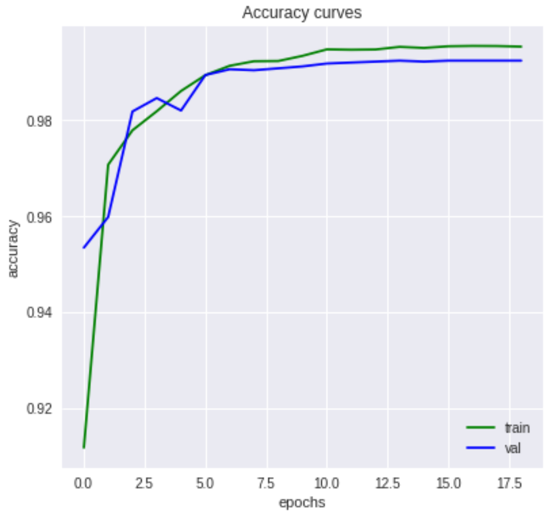


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.99515)
('best_acc_val', 0.9914)
('time_elapsed', 986.8798456192017)
('early_stopped', 15)
('epoch_passed', 20)

================= model10: Net5 =================
training model: Net5_0.5_0.0__YQ_10, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2241 acc: 91.17%   val lo
ss: 0.1285 acc: 95.34%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.0979 acc: 97.07%   val lo
ss: 0.1144 acc: 95.98%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0777 acc: 97.79%   val lo
ss: 0.0723 acc: 98.18%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0675 acc: 98.19%   val lo
ss: 0.0616 acc: 98.46%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0548 acc: 98.61%   val lo
ss: 0.0678 acc: 98.20%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0412 acc: 98.94%   val lo
ss: 0.0429 acc: 98.94%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0336 acc: 99.13%   val lo
ss: 0.0401 acc: 99.06%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0305 acc: 99.23%   val lo
ss: 0.0414 acc: 99.04%
[Epoch  8/29 100.00% 0m49s] train loss: 0.0284 acc: 99.23%   val lo
ss: 0.0394 acc: 99.08%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0262 acc: 99.34%   val lo
ss: 0.0378 acc: 99.12%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0204 acc: 99.48%   val lo
ss: 0.0350 acc: 99.18%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0203 acc: 99.47%   val lo
ss: 0.0353 acc: 99.20%   *
[Epoch 12/29 100.00% 0m49s] train loss: 0.0196 acc: 99.47%   val lo
ss: 0.0351 acc: 99.22%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0186 acc: 99.53%   val lo
ss: 0.0355 acc: 99.24%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0188 acc: 99.50%   val lo
ss: 0.0360 acc: 99.22%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0179 acc: 99.54%   val lo
ss: 0.0359 acc: 99.24%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0178 acc: 99.55%   val lo
ss: 0.0359 acc: 99.24%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0177 acc: 99.54%   val lo
ss: 0.0360 acc: 99.24%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0177 acc: 99.53%   val lo
```

```
ss: 0.0361 acc: 99.24%   s
Early stop at epoch: 14
Training complete in 15m 38s
Best val Acc on val:   99.24%
Best val Acc on train: 99.55%
```

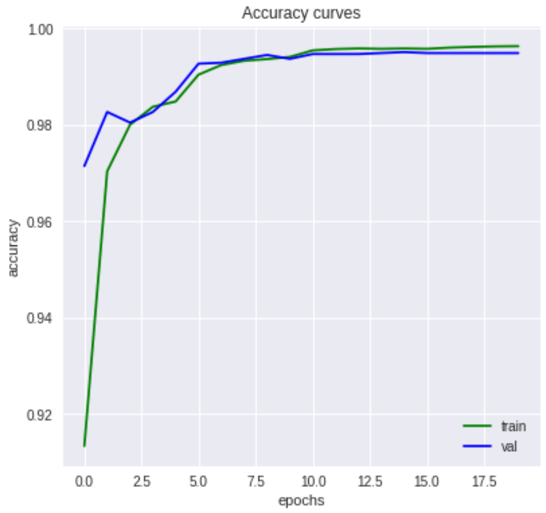




```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995475)
('best_acc_val', 0.9924)
('time_elapsed', 938.423749923706)
('early_stopped', 14)
('epoch_passed', 19)

================== model11: Net5 ==================
training model: Net5_0.5_0.0__YQ_11, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2167 acc: 91.34%   val lo
ss: 0.1018 acc: 97.14%   *
[Epoch  1/29 100.00% 0m50s] train loss: 0.0982 acc: 97.03%   val lo
ss: 0.0664 acc: 98.26%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0720 acc: 98.00%   val lo
ss: 0.0746 acc: 98.04%
[Epoch  3/29 100.00% 0m49s] train loss: 0.0614 acc: 98.37%   val lo
ss: 0.0598 acc: 98.26%
[Epoch  4/29 100.00% 0m49s] train loss: 0.0565 acc: 98.48%   val lo
ss: 0.0534 acc: 98.68%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0376 acc: 99.03%   val lo
ss: 0.0328 acc: 99.26%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0308 acc: 99.23%   val lo
ss: 0.0291 acc: 99.28%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0278 acc: 99.32%   val lo
ss: 0.0272 acc: 99.36%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0257 acc: 99.36%   val lo
ss: 0.0267 acc: 99.44%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0236 acc: 99.40%   val lo
ss: 0.0282 acc: 99.36%   s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0192 acc: 99.53%   val lo
ss: 0.0262 acc: 99.46%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0182 acc: 99.56%   val lo
ss: 0.0261 acc: 99.46%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0178 acc: 99.58%   val lo
ss: 0.0260 acc: 99.46%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0175 acc: 99.57%   val lo
ss: 0.0260 acc: 99.48%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0172 acc: 99.58%   val lo
ss: 0.0261 acc: 99.50%   * s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0167 acc: 99.57%   val lo
ss: 0.0262 acc: 99.48%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0162 acc: 99.59%   val lo
ss: 0.0263 acc: 99.48%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0161 acc: 99.61%   val lo
ss: 0.0264 acc: 99.48%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0157 acc: 99.62%   val lo
```

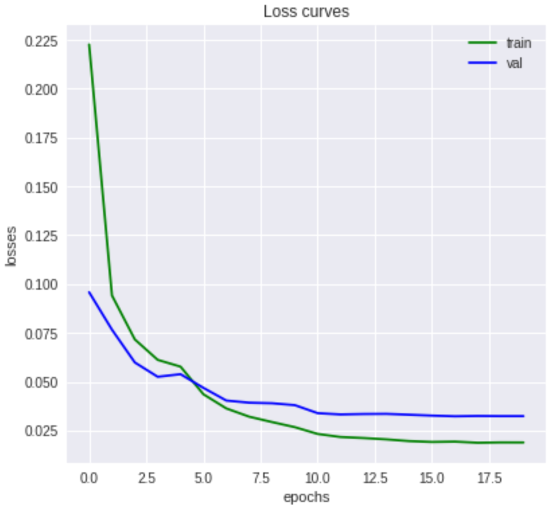
```
ss: 0.0265 acc: 99.48%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0155 acc: 99.62%   val lo
ss: 0.0266 acc: 99.48%   s
Early stop at epoch: 15
Training complete in 16m 29s
Best val Acc on val:   99.50%
Best val Acc on train: 99.62%
```

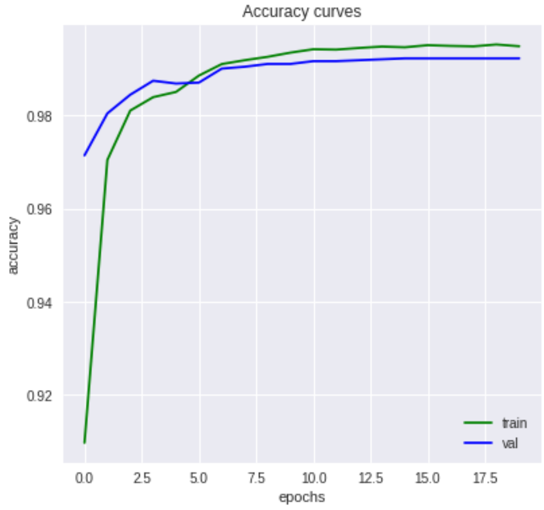


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.996225)
('best_acc_val', 0.995)
('time_elapsed', 988.7064473628998)
('early_stopped', 15)
('epoch_passed', 20)

================== model12: Net5 ==================
training model: Net5_0.5_0.0__YQ_12, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2227 acc: 90.98%   val lo
ss: 0.0958 acc: 97.14%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.0941 acc: 97.04%   val lo
ss: 0.0766 acc: 98.04%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0716 acc: 98.10%   val lo
ss: 0.0598 acc: 98.44%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0612 acc: 98.39%   val lo
ss: 0.0525 acc: 98.74%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0577 acc: 98.50%   val lo
ss: 0.0538 acc: 98.68%   s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0436 acc: 98.85%   val lo
ss: 0.0468 acc: 98.70%
[Epoch  6/29 100.00% 0m49s] train loss: 0.0363 acc: 99.10%   val lo
ss: 0.0403 acc: 99.00%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0321 acc: 99.18%   val lo
ss: 0.0392 acc: 99.04%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0293 acc: 99.25%   val lo
ss: 0.0390 acc: 99.10%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0267 acc: 99.34%   val lo
ss: 0.0380 acc: 99.10%   s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0232 acc: 99.41%   val lo
ss: 0.0339 acc: 99.16%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0217 acc: 99.41%   val lo
ss: 0.0332 acc: 99.16%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0211 acc: 99.44%   val lo
ss: 0.0335 acc: 99.18%   *
[Epoch 13/29 100.00% 0m49s] train loss: 0.0205 acc: 99.47%   val lo
ss: 0.0335 acc: 99.20%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0196 acc: 99.46%   val lo
ss: 0.0331 acc: 99.22%   * s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0191 acc: 99.50%   val lo
ss: 0.0326 acc: 99.22%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0193 acc: 99.49%   val lo
ss: 0.0323 acc: 99.22%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0187 acc: 99.48%   val lo
ss: 0.0324 acc: 99.22%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0189 acc: 99.52%   val lo
```

```
ss: 0.0324 acc: 99.22%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0189 acc: 99.48%   val lo
ss: 0.0324 acc: 99.22%   s
Early stop at epoch: 15
Training complete in 16m 26s
Best val Acc on val:   99.22%
Best val Acc on train: 99.52%
```

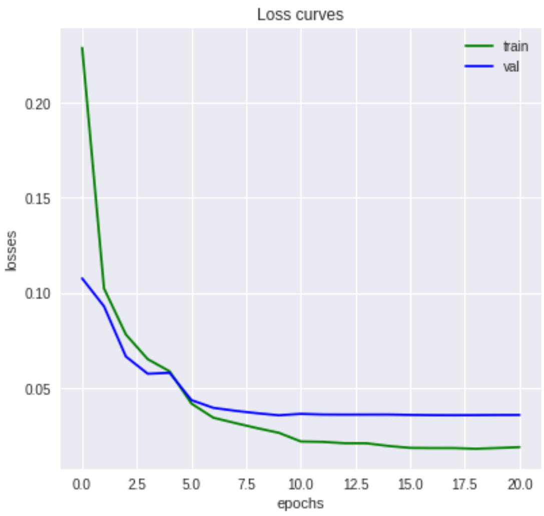


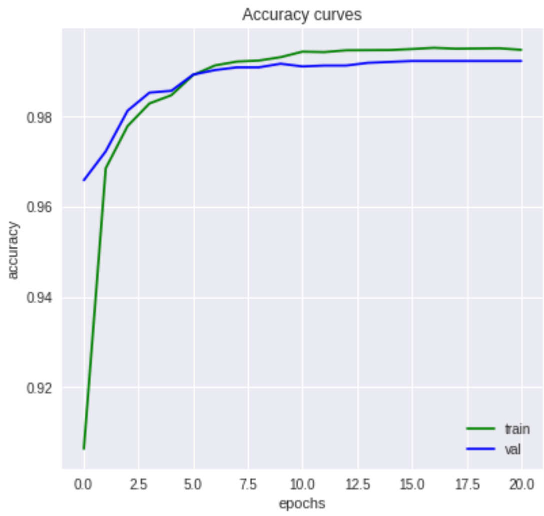


```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995175)
('best_acc_val', 0.9922)
('time_elapsed', 986.0299928188324)
('early_stopped', 15)
('epoch_passed', 20)

================== model13: Net5 ==================
training model: Net5_0.5_0.0__YQ_13, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2288 acc: 90.63%   val lo
ss: 0.1077 acc: 96.58%   *
[Epoch  1/29 100.00% 0m49s] train loss: 0.1024 acc: 96.84%   val lo
ss: 0.0930 acc: 97.22%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0782 acc: 97.78%   val lo
ss: 0.0667 acc: 98.12%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0652 acc: 98.28%   val lo
ss: 0.0576 acc: 98.52%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0589 acc: 98.46%   val lo
ss: 0.0581 acc: 98.56%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0419 acc: 98.91%   val lo
ss: 0.0437 acc: 98.92%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0345 acc: 99.12%   val lo
ss: 0.0397 acc: 99.02%   *
[Epoch  7/29 100.00% 0m49s] train loss: 0.0317 acc: 99.21%   val lo
ss: 0.0381 acc: 99.08%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0290 acc: 99.23%   val lo
ss: 0.0368 acc: 99.08%
[Epoch  9/29 100.00% 0m49s] train loss: 0.0266 acc: 99.30%   val lo
ss: 0.0358 acc: 99.16%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0220 acc: 99.43%   val lo
ss: 0.0365 acc: 99.10%
[Epoch 11/29 100.00% 0m49s] train loss: 0.0218 acc: 99.42%   val lo
ss: 0.0362 acc: 99.12%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0211 acc: 99.46%   val lo
ss: 0.0361 acc: 99.12%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0211 acc: 99.46%   val lo
ss: 0.0361 acc: 99.18%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0197 acc: 99.46%   val lo
ss: 0.0362 acc: 99.20%   * s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0186 acc: 99.48%   val lo
ss: 0.0360 acc: 99.22%   *
[Epoch 16/29 100.00% 0m49s] train loss: 0.0185 acc: 99.51%   val lo
ss: 0.0359 acc: 99.22%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0185 acc: 99.49%   val lo
ss: 0.0358 acc: 99.22%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0182 acc: 99.50%   val lo
```

```
ss: 0.0359 acc: 99.22%
[Epoch 19/29 100.00% 0m49s] train loss: 0.0186 acc: 99.50%   val lo
ss: 0.0359 acc: 99.22%   s
[Epoch 20/29 100.00% 0m49s] train loss: 0.0190 acc: 99.47%   val lo
ss: 0.0359 acc: 99.22%   s
Early stop at epoch: 16
Training complete in 17m 16s
Best val Acc on val:   99.22%
Best val Acc on train: 99.51%
```

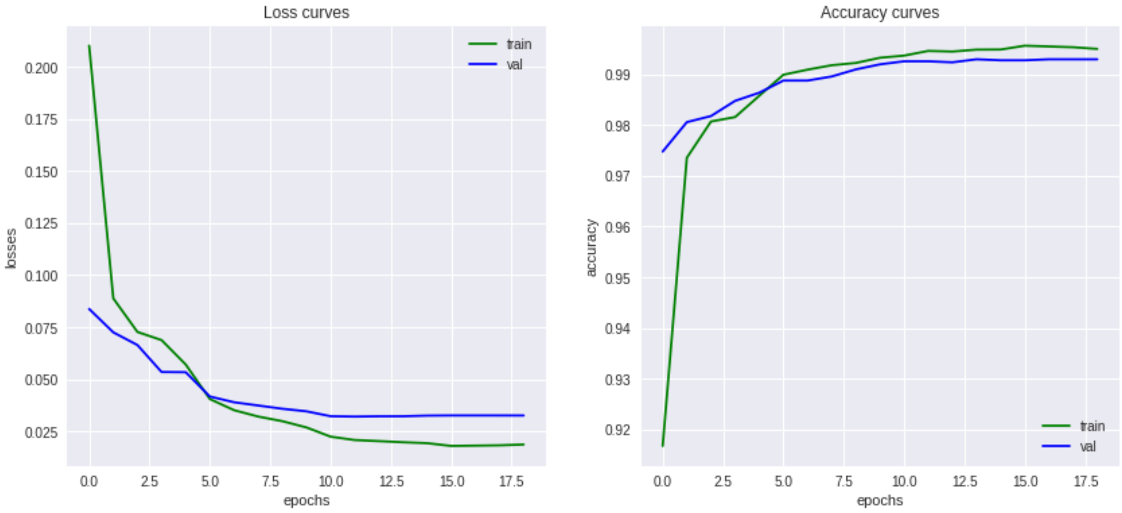




```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995125)
('best_acc_val', 0.9922)
('time_elapsed', 1036.3160514831543)
('early_stopped', 16)
('epoch_passed', 21)

================== model14: Net5 ==================
training model: Net5_0.5_0.0__YQ_14, lr: 0.001, weight_decay:0
shuffling train_valid_set before splitting... complete.
split train_valid_set to 40000 / 5000 samples
train_set size:40000, valid_set size:5000
's': auto saved, '*': best accuracy so far.
[Epoch  0/29 100.00% 0m50s] train loss: 0.2102 acc: 91.67%   val lo
ss: 0.0838 acc: 97.48%   *
[Epoch  1/29 100.00% 0m50s] train loss: 0.0888 acc: 97.36%   val lo
ss: 0.0725 acc: 98.06%   *
[Epoch  2/29 100.00% 0m49s] train loss: 0.0727 acc: 98.07%   val lo
ss: 0.0664 acc: 98.18%   *
[Epoch  3/29 100.00% 0m49s] train loss: 0.0688 acc: 98.16%   val lo
ss: 0.0535 acc: 98.48%   *
[Epoch  4/29 100.00% 0m49s] train loss: 0.0571 acc: 98.58%   val lo
ss: 0.0534 acc: 98.64%   * s
[Epoch  5/29 100.00% 0m49s] train loss: 0.0405 acc: 99.00%   val lo
ss: 0.0417 acc: 98.88%   *
[Epoch  6/29 100.00% 0m49s] train loss: 0.0352 acc: 99.09%   val lo
ss: 0.0390 acc: 98.88%
[Epoch  7/29 100.00% 0m49s] train loss: 0.0321 acc: 99.18%   val lo
ss: 0.0374 acc: 98.96%   *
[Epoch  8/29 100.00% 0m49s] train loss: 0.0299 acc: 99.23%   val lo
ss: 0.0358 acc: 99.10%   *
[Epoch  9/29 100.00% 0m49s] train loss: 0.0269 acc: 99.33%   val lo
ss: 0.0346 acc: 99.20%   * s
[Epoch 10/29 100.00% 0m49s] train loss: 0.0224 acc: 99.37%   val lo
ss: 0.0323 acc: 99.26%   *
[Epoch 11/29 100.00% 0m49s] train loss: 0.0208 acc: 99.47%   val lo
ss: 0.0321 acc: 99.26%
[Epoch 12/29 100.00% 0m49s] train loss: 0.0203 acc: 99.45%   val lo
ss: 0.0322 acc: 99.24%
[Epoch 13/29 100.00% 0m49s] train loss: 0.0198 acc: 99.49%   val lo
ss: 0.0322 acc: 99.30%   *
[Epoch 14/29 100.00% 0m49s] train loss: 0.0193 acc: 99.49%   val lo
ss: 0.0326 acc: 99.28%   s
[Epoch 15/29 100.00% 0m49s] train loss: 0.0180 acc: 99.57%   val lo
ss: 0.0326 acc: 99.28%
[Epoch 16/29 100.00% 0m49s] train loss: 0.0181 acc: 99.55%   val lo
ss: 0.0326 acc: 99.30%
[Epoch 17/29 100.00% 0m49s] train loss: 0.0183 acc: 99.54%   val lo
ss: 0.0326 acc: 99.30%
[Epoch 18/29 100.00% 0m49s] train loss: 0.0187 acc: 99.50%   val lo
```

```
ss: 0.0326 acc: 99.30%   s
Early stop at epoch: 14
Training complete in 15m 39s
Best val Acc on val:   99.30%
Best val Acc on train: 99.57%
```




```
('n_min_valid_set', 128)
('n_test_set', 5000)
('shuffle_before_split', True)
('use_norm', True)
('batch_size', 128)
('trainer', 'YQ')
('max_epochs', 30)
('early_stopping', True)
('epoch_patience', 5)
('auto_load_best_after_train', True)
('auto_save_interval', 5)
('show_live_progress', True)
('best_acc_train', 0.995675)
('best_acc_val', 0.993)
('time_elapsed', 938.8093650341034)
('early_stopped', 14)
('epoch_passed', 19)
```

1.6 Performance of models on reserved testing dataset

We also implemented some methods to make prediction and bagging.

In [0]:

```
def predict(model, test_X):
    """predict using a model on a dataset(test_X)
    params
        model: nn.Module
        test_X: dataset, narray (n_size, n_feature)
    returns
        predict_labels: prediction, list [n_size]
    """
    since = time.time()
    model.to(device)
    try:
        model.eval()   # Set model to evaluate mode
    except:
        pass
    predict_labels = []
    # Iterate over data.
    i = 0
    total = len(test_X)
    test_data = dataloader(phase = 'test', data_source = test_X,
                           img_size = NEW_IMG_SIZE)
    for batch_inputs in test_data:
        #debug(batch_inputs.shape)
        batch_inputs = batch_inputs.to(device)
        with torch.set_grad_enabled(False):
            batch_outputs = model(batch_inputs)
            batch_predict = torch.argmax(batch_outputs, dim = 1)
            batch_predict = batch_predict.cpu().numpy().tolist()
            predict_labels.extend(batch_predict)
            i += batch_inputs.size(0)
            print_progress(i / total)
    return predict_labels


def predicts_from_models(models, test_X):
    """return an ensemble predicts of all models on test_X
    params
        models: list [model]
        test_X: test set, narray (n_samples, n_features)
    returns
        predicts: narray (n_samples, len(models))
    """
    n_models = len(models)
    n_samples = test_X.shape[0]
    predicts = np.zeros((n_samples, n_models))
    for i, model in enumerate(models):
        predicts[:,i] = np.array(predict(model, test_X)).reshape(-1, )

    return predicts


def bagging(all_predicts):
    """giving a bagging predict based on all_predicts
    params
        all_predicts: narray (n_samples, n_models)
    returns
        voted_predict: list,
    """
    n_samples, n_models = all_predicts.shape
    voted_predict = [None] * n_samples
```

```
    for i in range(n_samples):
        voted_predict[i] = np.argmax(np.bincount(all_predicts[i].astype(int)))
    return voted_predict


def bagging_from_models(models, test_X):
    """ensemble predic using bagging
    params
        models: list of model of nn.Module, [nn.Module]
        test_X: dataset, narray (n_size, n_feature)
    returns
        voted_predicted: prediction, list [n_size]
        predicts: predicts by all models, narray [n_size, len(models)]
    """
    predicts = predicts_from_models(models, test_X)
    voted_predict = bagging(predicts)
    return voted_predict, predicts


def analysis_predict(true_labels, predict_labels, n_class = 31,
                     int_to_label = None):
    """give an averate accuracy, show accuracies in each class.
    you can switch the values of the two parameters to see difference output
    params
        true_labels: narray (-1, ) or (-1, 1)
        predict_labels: narray (-1, ) or (-1, 1)
    returns
        average_accuracy
    """
    debug("Size: {}".format(len(true_labels)))
    class_correct = [0 for _ in range(n_class)]
    class_total = [0 for _ in range(n_class)]
    for i in range(len(predict_labels)):
        label_int = int(true_labels[i])
        class_correct[label_int] += (predict_labels[i] == label_int)
        class_total[label_int] += 1

    average_accuracy = sum(class_correct) / sum(class_total)
    print("Average accuracy: {:.2%}".format(average_accuracy))

    print("-"*32)
    for i in range(n_class):
        s = int_to_label[i] if int_to_label else str(i)
        print("Accuracy of {:>12s}: {:.2%}({}/{})".format(
            str(i), class_correct[i] / class_total[i],
            class_correct[i], class_total[i]))

    return average_accuracy
```

In [17]:

```
voted_predict, all_predicts = bagging_from_models(models, test_set[:,:-1])
```

```
progress:100.00%
```

In [18]:

```
analysis_predict(test_set[:,-1], voted_predict, n_class = 2)
```

```
Size: 5000
Average accuracy: 99.28%
--------------------------------
Accuracy of           0: 98.55%(2451/2487)
Accuracy of           1: 100.00%(2513/2513)
```

Out[18]:

```
0.9928
```

In [19]:

```
for i in range(all_predicts.shape[1]):
    analysis_predict(test_set[:,-1], all_predicts[:,i], n_class = 2)
    print("")
```

```
Size: 5000
Average accuracy: 99.26%
--------------------------------
Accuracy of            0: 98.63%(2453/2487)
Accuracy of            1: 99.88%(2510/2513)

Size: 5000
Average accuracy: 99.18%
--------------------------------
Accuracy of            0: 98.39%(2447/2487)
Accuracy of            1: 99.96%(2512/2513)

Size: 5000
Average accuracy: 99.24%
--------------------------------
Accuracy of            0: 98.47%(2449/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 99.16%
--------------------------------
Accuracy of            0: 98.39%(2447/2487)
Accuracy of            1: 99.92%(2511/2513)

Size: 5000
Average accuracy: 99.26%
--------------------------------
Accuracy of            0: 98.55%(2451/2487)
Accuracy of            1: 99.96%(2512/2513)

Size: 5000
Average accuracy: 99.20%
--------------------------------
Accuracy of            0: 98.39%(2447/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 99.24%
--------------------------------
Accuracy of            0: 98.47%(2449/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 99.02%
--------------------------------
Accuracy of            0: 98.03%(2438/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 98.98%
--------------------------------
Accuracy of            0: 97.95%(2436/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 99.20%
--------------------------------
Accuracy of            0: 98.39%(2447/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
```

```
Average accuracy: 99.20%
--------------------------------
Accuracy of            0: 98.39%(2447/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 99.32%
--------------------------------
Accuracy of            0: 98.71%(2455/2487)
Accuracy of            1: 99.92%(2511/2513)

Size: 5000
Average accuracy: 99.16%
--------------------------------
Accuracy of            0: 98.31%(2445/2487)
Accuracy of            1: 100.00%(2513/2513)

Size: 5000
Average accuracy: 99.30%
--------------------------------
Accuracy of            0: 98.63%(2453/2487)
Accuracy of            1: 99.96%(2512/2513)

Size: 5000
Average accuracy: 99.18%
--------------------------------
Accuracy of            0: 98.35%(2446/2487)
Accuracy of            1: 100.00%(2513/2513)
```

1.7 Predict on Test Dataset

In this section, we can either use the models created during the training precedure or recreate the models and load their parameters from file paths. Skip the next 3 cells if the trained 12 models are alive; otherwise, run the next 3 cells to load models from files.

In [16]:

```
n_class = 2
NEW_IMG_SIZE = (28, 28)

models = []
for i in range(15):
    models.append(Net5(p_fc = 0.5, channels = [32, 64, 128, 128, 128]))
```

Out[16]:

```
'\nmodels = [\n    Net5(p_fc = 0.5, channels = [32, 64, 128, 128, 1
28]),\n    Net5(p_fc = 0.5, channels = [16, 32, 64, 64, 64]),\n    
Net5(p_fc = 0.5, channels = [8, 16, 32, 64, 64]),\n    Net5(p_fc = 
0.5, channels = [8, 16, 32, 64, 128]),\n    \n    Net5(p_fc = 0.6, 
channels = [32, 64, 128, 128, 128]),\n    Net5(p_fc = 0.6, channels
= [16, 32, 64, 64, 64]),\n    Net5(p_fc = 0.6, channels = [8, 16, 3
2, 64, 64]),\n    Net5(p_fc = 0.6, channels = [8, 16, 32, 64, 12
8]),\n    \n    Net5(p_fc = 0.4, channels = [32, 64, 128, 128, 12
8]),\n    Net5(p_fc = 0.4, channels = [16, 32, 64, 64, 64]),\n    N
et5(p_fc = 0.4, channels = [8, 16, 32, 64, 64]),\n    Net5(p_fc = 
0.4, channels = [8, 16, 32, 64, 128]),    \n]\n'
```

In [0]:

```
def load_model(model,
               best_model_path = None,
               auto_save_path = None,
               best_model_first = True,
               ext = "",
              ):
    """load a pre-trained model from a file path
    params
        model: model, nn.Module
        laod_best_model_first: Bool, if True, try first to load the model with
            parameters has best performance on validating set
        best_model_path: str
        auto_save_path: str
    return
        model: with pre_trained parameters loaded, if failed to load either
            parameters, return the model as it was.
    """

    if best_model_path is None:
        best_model_path = './models/best_model_' + model.get_name(ext)
    if auto_save_path is None:
        auto_save_path = './models/auto_save_' + model.get_name(ext)

    file_paths = [auto_save_path, best_model_path]
    if best_model_first:
        file_paths = [best_model_path, auto_save_path]

    try:
        debug("loading model from: '{}'... ".format(file_paths[0]), end=" ")
        model.load_state_dict(torch.load(file_paths[0]))
        debug("successful.")
    except:
        try:
            debug("failure.")
            debug("loading model from: '{}'... ".format(file_paths[1]), end = "
 ")
            model.load_state_dict(torch.load(file_paths[1]))
            debug("successful")
        except:
            debug("failure.\nusing new model parameters.")

    model = model.to(device)
    return model
```

In [18]:

```
for i, model in enumerate(models):
    model = load_model(model, None, None, True, ext = "_YQ_" + str(i))
```

```
loading model from: './models/best_model_Net5_0.5_0.0__YQ_0'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_1'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_2'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_3'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_4'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_5'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_6'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_7'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_8'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_9'...  su
ccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_10'...  s
uccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_11'...  s
uccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_12'...  s
uccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_13'...  s
uccessful.
loading model from: './models/best_model_Net5_0.5_0.0__YQ_14'...  s
uccessful.
```

We load test dataset from a file. Test dataset has 8000 examples, each containing a vector with 784 dimensions, without a label.

In [0]:

```
test_data = np.loadtxt("PATCH_test.amat")
# test_X, test_y = test_data[:,:-1], test_data[:, -1]
test_X = test_data
```

In [20]:

```
print(test_X.shape)#, test_y.shape)
```

```
(8000, 784)
```

We use the following code to make a bagging prediction on test dataset

In [21]:

```
bagging_predict, all_predicts = bagging_from_models(models, test_data)
```

```
progress:100.00%
```

Finally, we export our prediction to a csv file. In the csv file, there are altegother 8000 lines; each line has only one integer indicating the predicted class of the corresponding line of example in test dataset.

In [0]:

```
import csv

def predicts_to_csv(predicts, file_path):
    with open(file_path, 'w', newline='') as csvfile:
        writer = csv.writer(csvfile, delimiter = ',')
        #writer.writerow(("Id", "Category"))
        for i, label in enumerate(predicts):
            writer.writerow((predicts[i], ))
            #writer.writerow((i, int_to_label[predicts[i]]))
    debug(" save csv files to: {}".format(file_path))
```

In [32]:

```
current_model_name = "final_predict"
bagging_file_path = './submissions/' + current_model_name + ".csv"
predicts_to_csv(bagging_predict, bagging_file_path)
```

```
 save csv files to: ./submissions/final_predict.csv
```

We can also save all 12 models' predictions:

In [24]:

```
for i, model in enumerate(models):
    file_path = "./submissions/" + model.get_name("YQ") + "_" + str(i) + ".csv"
    pred = predict(model, test_X)
    predicts_to_csv(pred, file_path)
```

```
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
0.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
1.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
2.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
3.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
4.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
5.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
6.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
7.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
8.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_
9.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_1
0.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_1
1.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_1
2.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_1
3.csv
progress:100.00% save csv files to: ./submissions/Net5_0.5_0.0_YQ_1
4.csv
```

The first 1000 lines of the csv file are:

In [33]:

```
test_predict = np.loadtxt(bagging_file_path)
print(test_predict[0:1000])
```

```
[0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1.
1. 1.
 0. 0. 0. 0. 0. 0. 1. 0. 0. 1. 0. 1. 0. 1. 1. 1. 1. 1. 1. 0. 0. 1.
1. 1.
 0. 0. 1. 1. 1. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 1. 1. 1. 0. 0. 0. 1.
1. 1.
 1. 0. 1. 1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 0. 0. 1. 1. 0. 1. 0. 0. 0.
0. 1.
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0. 0.
 0. 1. 0. 1. 0. 1. 0. 0. 1. 1. 0. 0. 1. 1. 0. 1. 1. 0. 0. 1. 0. 1.
0. 0.
 1. 1. 1. 1. 0. 0. 1. 1. 0. 0. 1. 0. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1.
0. 1.
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1. 0.
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1. 0.
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0. 0.
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```

```
0. 1.
 1. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1. 1. 0. 0. 1. 0. 1. 0. 1. 0. 0.
0. 1.
 1. 1. 0. 1. 1. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0.
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0. 0.
 1. 0. 0. 0. 1. 1. 1. 1. 1. 0. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0.
1. 1.
 1. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 1. 0. 0. 1. 1. 0. 0. 1. 1. 0. 0.
1. 0.
 0. 1. 0. 0. 1. 1. 1. 0. 0. 1. 0. 1. 1. 0. 1. 1. 0. 0. 1. 1. 0. 1.
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1. 1.
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0. 1.
 1. 1. 0. 1. 0. 0. 1. 1. 0. 0. 1. 1. 1. 1. 0. 1. 1. 0. 0. 0. 1. 0.
0. 0.
 1. 0. 0. 1. 0. 0. 0. 1. 0. 1. 1. 1. 0. 0. 1. 1.]
```

The end of Question 1

---

2. Question 2

Answer

MapReduce - distribute method

For solving below problems, we considering adopting MapReduce method which could be used to run the job parrally on these 300 servers. With this method, we could redundantly distribute files by block (HDFS, Hadoop Distributed File System), distribute the calculation, maximize the proximity of computing units and disks, with MapReduce parallel programming paradigm.

This method includes two phases: Map and Reduce. Before sending data to the mapper, first convert it into key-value pairs. Because mapper only key-value pairs of data. Each phase has key-value as input and output.

- Map: (k, v) -> <k', v'>: In parallel, extract relevant information from each block.

Take a key-value pair and generate a set of key-value pairs.

- Reduce: (k', <v'>) -> <k', v''>: Join, combine, summarize partial results

All values v' with the same key K' are grouped together.

There is a call to a reduction function for each unique key K

2.1 Find the nearest 1000 pairs of twin stars (Euclidean distance from the position)

We would use MapReduce to solve this problem. From the data, we could know: luminance, physical_features, coordinates: (x,y,z)

Let's give the definition of twin stars: their age and their common properties suggest that they were born together, before dispersing in the Universe. We would use the luminance and physical_features to find them.

Step 1: Map: {star_id: luminance, physical_features}

Step 2: Reduce: with same luminance and physical_features, we group them to one pair star. {pair_star_id: star_id_1, star_id_2}

In our case, the location of each star is already known in the data set，let us give $p = (p_x, p_y, p_z)$ and $q = (q_x, q_y, q_z)$ are two points in Euclidean n-space, then the distance (d) from p to q, or from q to p is given by:

$$d(p, q) = d(q, p) = \sqrt{(q_x - p_x)^2 + (q_y - p_y)^2 + (q_z - p_z)^2}$$

Step 3: Calculate the distance between each twin star with their coordinates: (x,y,z)

Step 4: Map again with the distance: {pair_star_id: distance} sorted by distance acsending

Step 5: Select firth 1000th pair_star from the dictionary and write the resulting pairs in files

All phases are distributed in many tasks

2.2 Count how many stars there are in each category.

Here we could use Map-Reduce method to sort the star category in each server, then combine and count the stars there are in each category.

In [0]:

```
def Map(key, values):
// key: star_id; value: category
    for each star s in server[i]:
        emit(category, i)

def reduce(key, values):
// key: category; value: an iterator over counts
    result = 0
    for each count v in values:
        result += v
    emit(key, result)
```

2.3 Produce a classifier that, given the feature vector (22 real numbers), predicts the category of the star.

It's a classification problem. Now the task is to predict the category of the star with the given feature vector (22 real numbers). We would consider below processing in generating a Random Forest classifier with large scale data:

Step 1: Input data stored in distributed file system and divided into contiguous blocks.

Step 2: Map: input data with {label: 22 features}

Step 3: Selected random features and train a decision tree in each server

Step 4: Reduce: For unseen data, predict the category paralle in each server

Step 5: Finally give a majority vote to provide the final prediction.

---

3. Question 3

Expliquez en détail comment utiliser un classifieur binaire, capable d'apprendre à effectuer la classification de deux catégories, pour réaliser la classification dans un contexte ou plusieurs catégories doivent être distinguées. Considérez le cas à 3, 25, 12500 catégories et faite le contraste entre les différentes approches étudiées et le nombre de catégories.

Answer

In data science and machine learning, classification is a task for identifying to which of a set of categories a new observation belongs. Classification tasks are widely used in real world applications. Many of them involve more than two classes, that is multi-class problem. Usually, it is easier to build a classifier to distinguish only between two classes than to consider more than two classes in a problem, since the decision boundaries in the former case can be simpler. This is why binarization techniques have come up to deal with multi-class problems by dividing the original problem into easier to solve binary classification problems that are faced by binary classifiers. These classifiers are usually referred to as base learners or base classifiers of the system.

Approaches

There are many methods to reduce a multiclass problem to multiple binary classification problems. For all of these methods, after the binary classification problems have been solved, then we need to combine the results of binary classifiers in some way to get a final result of multi-class problem.

●One-vs-All (OVA)

OVA strategy trains a single classifier for each class. A proper technique can be used for building binary classifiers (e.g., Regularized Least Squares Classification, SVM) then we build n different binary classifiers. For the ith classifier, all the points in class i are the positive examples and all the points not in class i are the negative examples. Suppose f_i is the ith classifier and $f_i(\mathrm{x})$ is the score of ith classifier with an input x.

Then, any multi-class problem can resolved with following equation:

$$f(\mathrm{x}) = \arg\max_i \ f_i(\mathrm{x})$$

It return class index i which has the highest score with the input x.

●One-vs-One(OVO)

It is also called All-Pairs or All-vs-All classification. This method consists in fitting one classifier per class pair.

OVO builds $\frac{n(n-1)}{2}$ classifiers, one classifier to distinguish each pair of classes i and j. Let f_{ij} be the classifier where class i were positive examples and class j were negative.

Then, we can classify a multi-class problem with the equation:

$$f(\mathrm{x}) = \arg\max_i \ \left(\sum_j f_{ij}(\mathrm{x})\right).$$

The class which received the most votes is selected.

Approach comparison

The selection between OVA and OVO is mainly computational. Since OVO requires $\frac{n(n-1)}{2}$ classifiers, on the other hand, OVA only needs n classifiers.

Considering cases with 3, 25 and 12500 categories, we can get following contrast in a table by quantifying complexity of the two approaches with number of classifiers.

#Class	OVA	OVO
3	3	3
25	25	300
12500	12500	78118750

So OVO is usually slower than OVA, due to its $O(n^2)$ complexity. Especially when the number of classes are very huge, we would always prefer to use OVA.

4. Question 4

Faites une analyse détaillée et exhaustive des patrons existants dans le jeu de données adulte. Il est possible que le regroupement de valeurs pour certaines caractéristiques donne des résultat intéressant. Vous devez aussi, s'il y a lieux, discuter de l'aspect éthique concernant l'utilisation des patrons obtenus.

Answer

4.1 Loading Adult Income Data

In [0]:

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv
```

In [0]:

```
trainset_path = 'adult.data'
names = [
        "Age", "Workclass", "fnlwgt", "Education", "Education-Num", "Martial Sta
tus",
        "Occupation", "Relationship", "Race", "Sex", "Capital Gain", "Capital Lo
ss",
        "Hours per week", "Country", "Target"]

train_df = pd.read_table(trainset_path, sep = ', ', names = names, engine = 'pyt
hon', na_values = "?")
```

In [38]:

```
print(train_df.shape)
train_df.head(10)
```

(32561, 15)

Out[38]:

	Age	Workclass	fnlwgt	Education	Education-Num	Martial Status	Occupation	Relationship	Ra
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	Wh
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	Wh
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	Wh
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Bla
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Bla
5	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	Wh
6	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Bla
7	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	Wh
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	Wh
9	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	Wh

4.2 Categorizing Features of Continuous Variables

In the dataset, there are 6 features which accept continuous values; they are: 'Ages', 'fnlwgt', 'Education-Num', 'Capital Gain', 'Capital Loss', 'Hours per week'. We noticed that feature 'Education-Num' and another categorical feature: 'Education' are redundant, so we remove the feature 'Education-Num'. For the rest 5 features, we categorize them so as to reduce the product numbers and to find meaningful patrons.

To categorize an continuous feature, we first observe their basic statistic information using method `statistics` , then make a category list by using method `int2categorical` and replace the original value with catogorized value by using method `categorize` .

If we use market model to describe the dataset, each example in the dataset represents a transaction or a history record; value of a feature represents a product. Different from standard market model, same values in in different features represent different products. So we need to assign different catogorized name to the same values in different features. In method `int2categorial` , we use a parameter `prefix` to differentiate the same values in different features.

Here are the methods we implemented:

In [0]:

```
def int2categorical(values: list = None, prefix = ""):
    if values is None or len(values) == 0:
        return []
    categories = []
    if len(values) > 1:
        for i in range(len(values)-1):
            categories.append(prefix + "{}-{}".format(values[i], values[i+1]))
    return categories

def statistics(column_label: str, df: pd.DataFrame):
    df[column_label].hist()
    print(df[column_label].describe())

def categorize(column_label, values, categories, df):
    new_col_label = column_label # + "_cat"
    df[new_col_label] = pd.cut(df[column_label], values, right = False, labels =
 categories)
```

We remove the feature 'Education-Num'.

In [0]:

```
del train_df["Education-Num"]
```

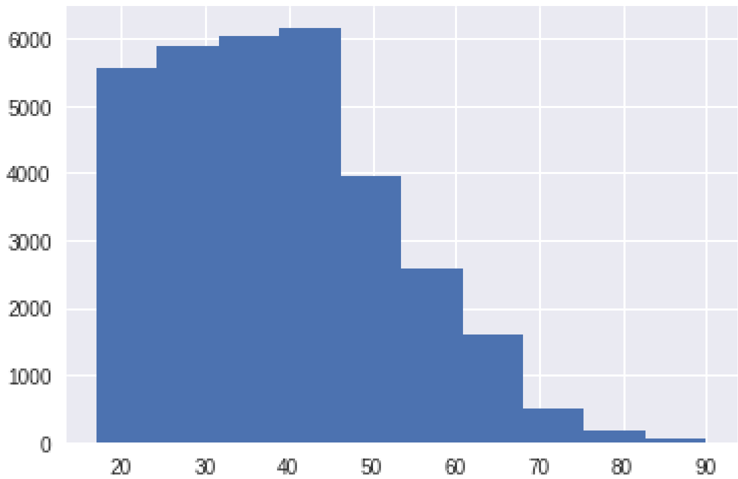
For the other 5 continuous features, we categorize them.

Age

In [41]:

```
label = "Age"
statistics(label, train_df)
```

```
count    32561.000000
mean        38.581647
std         13.640433
min         17.000000
25%         28.000000
50%         37.000000
75%         48.000000
max         90.000000
Name: Age, dtype: float64
```



In [0]:

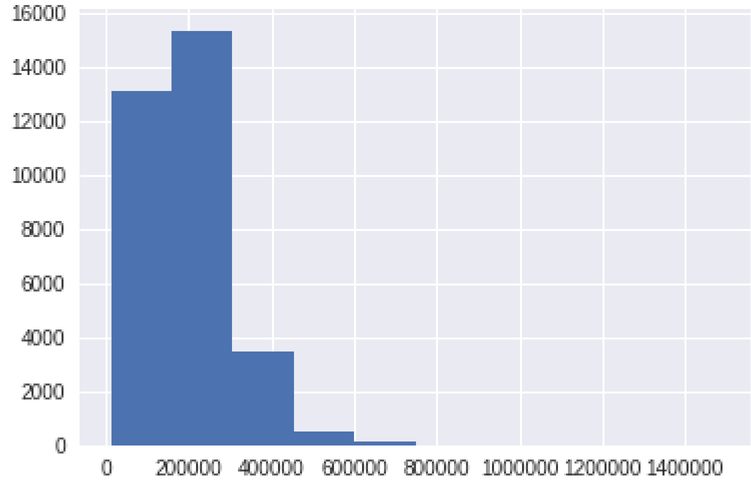
```
values = [0, 18, 30, 40, 50, 60, 70, 80, 90, 100]
labels = int2categorical(values, prefix = "age_")
categorize(label, values, labels, train_df)
```

fnlwgt

In [43]:

```
label = "fnlwgt"
statistics(label, train_df)
```

```
count    3.256100e+04
mean     1.897784e+05
std      1.055500e+05
min      1.228500e+04
25%      1.178270e+05
50%      1.783560e+05
75%      2.370510e+05
max      1.484705e+06
Name: fnlwgt, dtype: float64
```



In [0]:

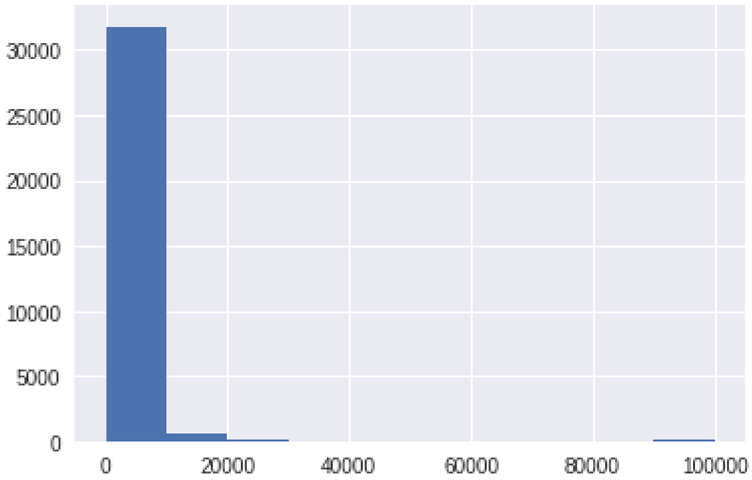
```
values = np.arange(0, 1600000, 100000)
labels = int2categorical(values, prefix = "fnlwgt_")
categorize(label, values, labels, train_df)
```

Capital Gain

In [45]:

```
label = "Capital Gain"
statistics(label, train_df)
```

```
count    32561.000000
mean      1077.648844
std       7385.292085
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max      99999.000000
Name: Capital Gain, dtype: float64
```



In [0]:

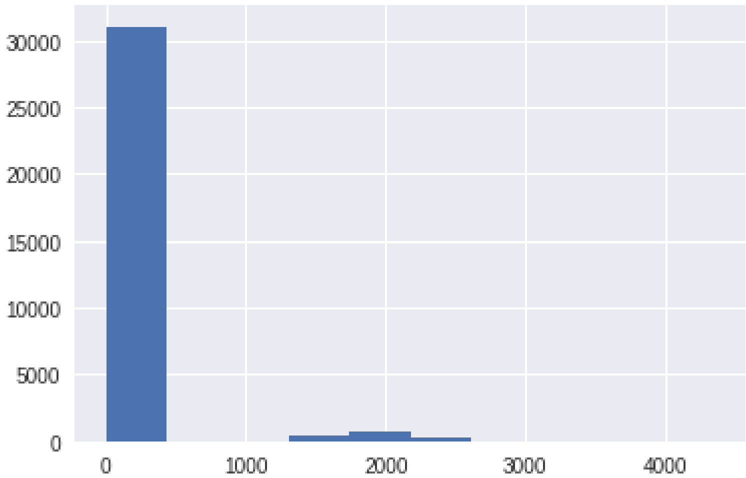
```
values = [0, 1, 10, 100, 1000, 10000, 100000]
labels = int2categorical(values, prefix = "CG_")
categorize(label, values, labels, train_df)
```

Capital Loss

In [47]:

```
label = "Capital Loss"
statistics(label, train_df)
```

```
count    32561.000000
mean        87.303830
std        402.960219
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max       4356.000000
Name: Capital Loss, dtype: float64
```



In [0]:

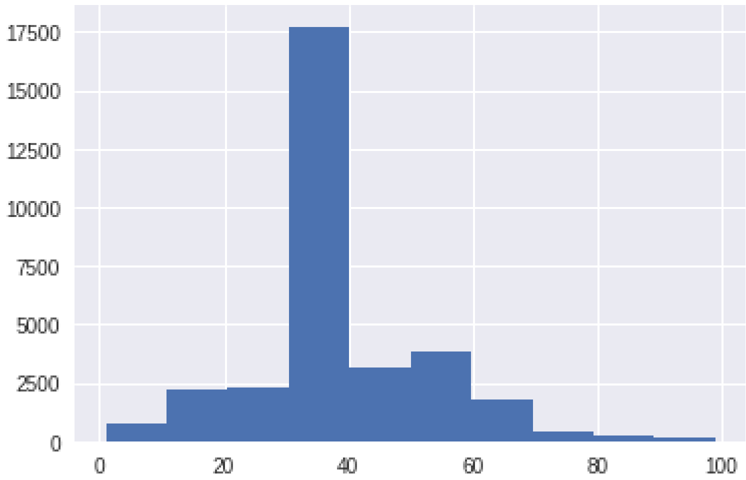
```
values = [0, 1, 10, 100, 1000, 10000, 100000]
labels = int2categorical(values, prefix = "CL_")
categorize(label, values, labels, train_df)
```

Hours per week

In [49]:

```
label = "Hours per week"
statistics(label, train_df)
```

```
count    32561.000000
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
Name: Hours per week, dtype: float64
```



In [0]:

```
values = [i for i in range(0, 100, 10)]
labels = int2categorical(values, prefix = "hpw_")
categorize(label, values, labels, train_df)
```

After categorizing, the data changes to the following forms(the first 20 examples):

In [51]:

```
train_df.head(20)
```

Out[51]:

	Age	Workclass	fnlwgt	Education	Martial Status	Occupation	Relationship	R
0	age_30-40	State-gov	fnlwgt_0-100000	Bachelors	Never-married	Adm-clerical	Not-in-family	W
1	age_50-60	Self-emp-not-inc	fnlwgt_0-100000	Bachelors	Married-civ-spouse	Exec-managerial	Husband	W
2	age_30-40	Private	fnlwgt_200000-300000	HS-grad	Divorced	Handlers-cleaners	Not-in-family	W
3	age_50-60	Private	fnlwgt_200000-300000	11th	Married-civ-spouse	Handlers-cleaners	Husband	B
4	age_18-30	Private	fnlwgt_300000-400000	Bachelors	Married-civ-spouse	Prof-specialty	Wife	B
5	age_30-40	Private	fnlwgt_200000-300000	Masters	Married-civ-spouse	Exec-managerial	Wife	W
6	age_40-50	Private	fnlwgt_100000-200000	9th	Married-spouse-absent	Other-service	Not-in-family	B
7	age_50-60	Self-emp-not-inc	fnlwgt_200000-300000	HS-grad	Married-civ-spouse	Exec-managerial	Husband	W
8	age_30-40	Private	fnlwgt_0-100000	Masters	Never-married	Prof-specialty	Not-in-family	W
9	age_40-50	Private	fnlwgt_100000-200000	Bachelors	Married-civ-spouse	Exec-managerial	Husband	W
10	age_30-40	Private	fnlwgt_200000-300000	Some-college	Married-civ-spouse	Exec-managerial	Husband	B
11	age_30-40	State-gov	fnlwgt_100000-200000	Bachelors	Married-civ-spouse	Prof-specialty	Husband	As I Isla
12	age_18-30	Private	fnlwgt_100000-200000	Bachelors	Never-married	Adm-clerical	Own-child	W
13	age_30-40	Private	fnlwgt_200000-300000	Assoc-acdm	Never-married	Sales	Not-in-family	B
14	age_40-50	Private	fnlwgt_100000-200000	Assoc-voc	Married-civ-spouse	Craft-repair	Husband	As I Isla
15	age_30-40	Private	fnlwgt_200000-300000	7th-8th	Married-civ-spouse	Transport-moving	Husband	Ar Inc Esk
16	age_18-30	Self-emp-not-inc	fnlwgt_100000-200000	HS-grad	Never-married	Farming-fishing	Own-child	W
17	age_30-40	Private	fnlwgt_100000-200000	HS-grad	Never-married	Machine-op-inspct	Unmarried	W
18	age_30-40	Private	fnlwgt_0-100000	11th	Married-civ-spouse	Sales	Husband	W

	Age	Workclass	fnlwgt	Education	Martial Status	Occupation	Relationship	R
19	age_40-50	Self-emp-not-inc	fnlwgt_200000-300000	Masters	Divorced	Exec-managerial	Unmarried	W

4.3 importing Frequent Pattern-Tree from Demo8

To find the frequent itemsets in the datasets, we use the algorithm: frequent patter tree. The class `FP_Tree` is implemented in Demo8; here we just use the class. We create a file: `fp_tree.py` containing the implementation of the class and put the file in current directory.

In [0]:

```
sys.path.append("/content/drive/My Drive/Colab Notebooks/IFT6758/TP2/")
from fp_tree import FP_Tree
```

4.4 Finding the frequent itemsets

Before using the class `FP_Tree` to find the frequent itemsets, we need first to construct the market from the history, which is the dataset, and to compute the frequent of each product in the dataset. These can be done by the following codes.

In [0]:

```
freq = {}
history = []
market = {}
idx = 0

for i, row in train_df.iterrows():
    list_row = row.tolist() # from series to list
    history.append(list_row)

    for product in list_row:
        if product not in market:
            market[product] = idx
            freq[idx] = 1
            idx += 1
        else:
            freq[market[product]] += 1


market_inv = {}
for key, value in market.items():
    market_inv[value] = key
```

Let's see how many products(different values) in the whole datasets:

In [70]:

```
print(len(market))
```

142

Let's see the frequent of each product:

In [71]:

```
def show_freq(market_inv, freq, s = 0):
    print("{:<30} {}".format("Product", "Freq"))
    print("-"*36)
    num = 0
    for key in freq:
        if freq[key] >= s:
            print("{:<30} {}".format(market_inv[key], freq[key]))
            num += 1
    print("-"*36)
    print("total: {} products".format(num))

show_freq(market_inv, freq, s = 0)
```

```
Product                         Freq
------------------------------------
age_30-40                       8613
State-gov                       1298
fnlwgt_0-100000                 5670
Bachelors                       5355
Never-married                   10683
Adm-clerical                    3770
Not-in-family                   8305
White                           27816
Male                            21790
CG_1000-10000                   1887
CL_0-1                          31042
hpw_40-50                       18336
United-States                   29170
<=50K                           24720
age_50-60                       4418
Self-emp-not-inc                2541
Married-civ-spouse              14976
Exec-managerial                 4066
Husband                         13193
CG_0-1                          29849
hpw_10-20                       1246
Private                         22696
fnlwgt_200000-300000            7976
HS-grad                         10501
Divorced                        4443
Handlers-cleaners               1370
11th                            1175
Black                           3124
age_18-30                       9316
fnlwgt_300000-400000            3148
Prof-specialty                  4140
Wife                            1568
Female                          10771
Cuba                            95
Masters                         1723
age_40-50                       7175
fnlwgt_100000-200000            14503
9th                             514
Married-spouse-absent           418
Other-service                   3295
Jamaica                         81
>50K                            7841
CG_10000-100000                 770
hpw_50-60                       3877
Some-college                    7291
hpw_80-90                       202
Asian-Pac-Islander              1039
India                           100
Own-child                       5068
hpw_30-40                       3667
Assoc-acdm                      1067
Sales                           3650
Assoc-voc                       1382
Craft-repair                    4099
nan                             4401
7th-8th                         646
Transport-moving                1597
Amer-Indian-Eskimo              311
Mexico                          643
```

```
Farming-fishing               994
Machine-op-inspct             2002
Unmarried                     3446
Doctorate                     413
hpw_60-70                     1796
Separated                     1025
hpw_20-30                     2392
Federal-gov                   960
CL_1000-10000                 1483
Tech-support                  928
Local-gov                     2093
South                         80
Protective-serv               649
Puerto-Rico                   114
fnlwgt_500000-600000          230
Married-AF-spouse             23
Other                         271
Prof-school                   576
Honduras                      13
Self-emp-inc                  1116
5th-6th                       333
hpw_70-80                     448
age_70-80                     508
Other-relative                981
age_60-70                     2015
10th                          933
hpw_0-10                      458
fnlwgt_400000-500000          892
England                       90
age_0-18                      395
Canada                        121
Germany                       137
Iran                          43
Widowed                       993
Philippines                   198
1st-4th                       168
fnlwgt_600000-700000          78
Italy                         73
Poland                        60
age_90-100                    43
Preschool                     51
Columbia                      59
Cambodia                      19
Thailand                      18
Ecuador                       28
Laos                          18
Taiwan                        51
fnlwgt_800000-900000          9
Haiti                         44
Portugal                      37
fnlwgt_1000000-1100000        5
12th                          433
Dominican-Republic            70
age_80-90                     78
CG_100-1000                   55
Armed-Forces                  9
El-Salvador                   106
France                        29
Priv-house-serv               149
Guatemala                     64
CL_100-1000                   36
```

```
China                          75
fnlwgt_700000-800000           35
Japan                          62
Yugoslavia                     16
Peru                           31
Outlying-US(Guam-USVI-etc)     14
Scotland                       12
fnlwgt_900000-1000000          7
Trinadad&Tobago                19
Greece                         29
Without-pay                    14
Nicaragua                      34
Vietnam                        67
Hong                           20
Ireland                        24
Never-worked                   7
fnlwgt_1100000-1200000         3
fnlwgt_1200000-1300000         2
Hungary                        13
fnlwgt_1400000-1500000         2
fnlwgt_1300000-1400000         1
Holand-Netherlands             1
------------------------------------
total: 142 products
```

Let's see how many products exist when we set the frequent threshold `s` to `10000`.

In [72]:

```
show_freq(market_inv, freq, s = 10000)
```

```
Product                        Freq
------------------------------------
Never-married                  10683
White                          27816
Male                           21790
CL_0-1                         31042
hpw_40-50                      18336
United-States                  29170
<=50K                          24720
Married-civ-spouse             14976
Husband                        13193
CG_0-1                         29849
Private                        22696
HS-grad                        10501
Female                         10771
fnlwgt_100000-200000           14503
------------------------------------
total: 14 products
```

We set the threshold `s = 10000` to build the Frequent Pattern Tree.

In [73]:

```
threshold = 10000
frequent_product = [k for k, v in freq.items() if v > threshold]
for id in frequent_product:
    print(market_inv[id], end = ", ")
print()
```

```
Never-married, White, Male, CL_0-1, hpw_40-50, United-States, <=50
K, Married-civ-spouse, Husband, CG_0-1, Private, HS-grad, Female, f
nlwgt_100000-200000,
```

In [0]:

```
import graphviz
from graphviz import Digraph
```

In [0]:

```
def test(history, subset = 10):
    fp_tree = FP_Tree()

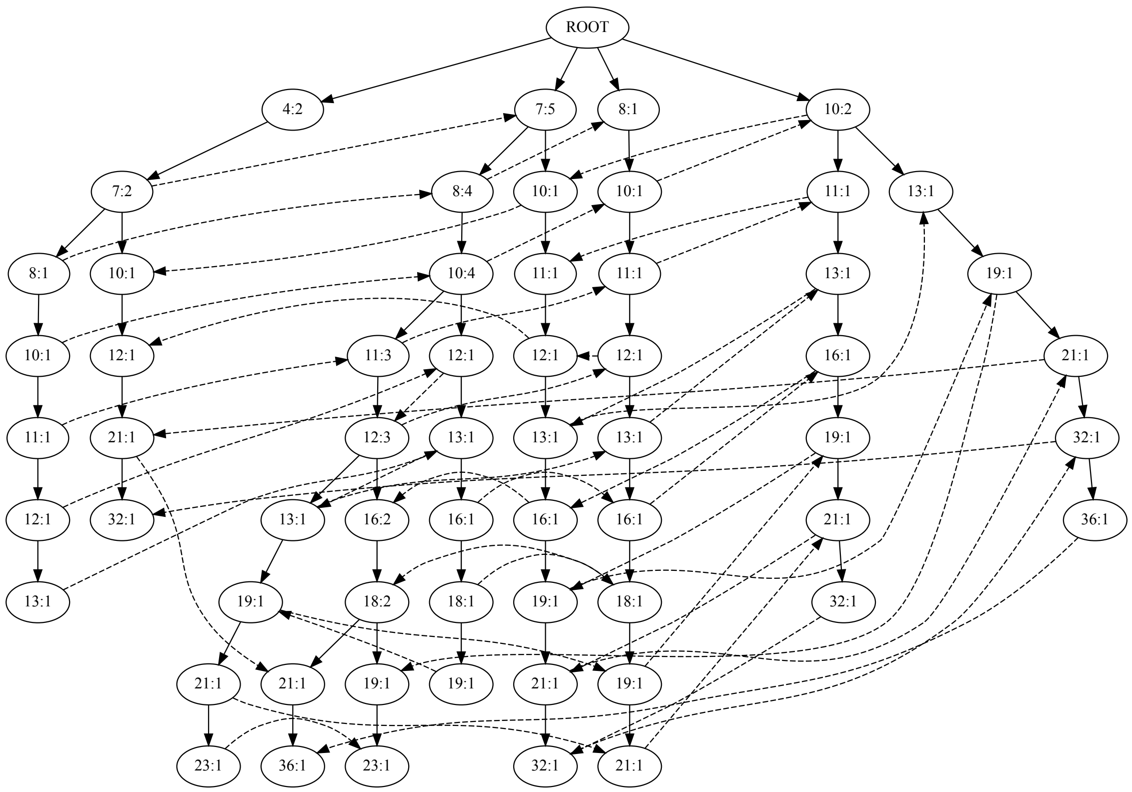
    for basket in history[:subset]:
        # on convertit les noms de produit en entier
        basket = [market[product] for product in basket if market[product] in fr
equent_product]
        # on trie les produits
        basket.sort()
        #on insère dans le trie un basket
        fp_tree.insert(basket)
    return fp_tree
```

As a pre-experiment, we use the first 10 transactions(examples) to show the FP tree built.

In [76]:

```
tree = test(history, 10)
tree.extract([], tree)
dot = tree.show(True)
graphviz.Source(dot)
```

Out[76]:



Now, we build the tree based on whole dataset.

In [77]:

```
%%time
tree = test(history, None)
```

```
CPU times: user 363 ms, sys: 3.2 ms, total: 366 ms
Wall time: 370 ms
```

4.5 Interpretation of the Results

We print all frequent patterns when threshold is `10000` .

In [78]:

```
tree.extract([], tree, s = threshold)
tree.itemsets
```

Out[78]:

```
[[4],
 [7],
 [7, 4],
 [8],
 [8, 4],
 [8, 7],
 [8, 7, 4],
 [10],
 [10, 4],
 [10, 7],
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 [12, 11, 10, 7, 4],
```

```
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```

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 [16, 13, 11, 10, 8, 7],
```

```
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    [16, 11, 8],
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    [16, 11, 10, 8],
    [16, 11, 10, 8, 7],
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    [18, 12, 10, 7],
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```

There are altogether 6655 frequent patterns when threshold is set `10000` .

In [79]:

```
print(len(tree.itemsets))
```

```
6655
```

Each of the 6655 patterns acquired is a list of integer; each integer represents the id of a product in the market. We can translate the ids to their names to have a clear understanding of the patterns found. The dictionary `market_inv` helps to do such translation.

We can also only show the frequent pattern with the list length no less than a certain value:

In [0]:

```
def show_frequent_products(length = 4):
    frequent_itemsets = []
    for itemset in tree.itemsets:
        if len(itemset) < length:
            continue
        freq_item = []
        for item in itemset:
            freq_item.append(market_inv[item])
        frequent_itemsets.append(freq_item)
        print(freq_item)
    print("{} frequent pattern(s) with products length >= {}".format(
        len(frequent_itemsets), length))
    #return frequent_itemsets
```

When `length = 12`, we get the longest frequent pattern:

In [83]:

```
show_frequent_products(length = 12)
```

```
['fnlwgt_100000-200000', 'HS-grad', 'Private', 'CG_0-1', 'Husband',
'Married-civ-spouse', '<=50K', 'United-States', 'hpw_40-50', 'CL_0-
1', 'Male', 'White']
1 frequent pattern(s) with products length >= 12
```

We can decrease the threshold to get more frequent patterns. The number of the frequent patterns will increase as the threhold decreases, and it will take more time to obtain these frequent patterns if the threshold decrease. In the report, we only examined the frequent patterns when threshold is `10000`, which is just a demostration.

4.6 Ethic Concerning on the Use of the Patterns Acquired

Having the most frequent patterns in Adult Income dataset, people can come to some interesting findings. According to the longest frequent pattern we found, for example, one may say that most U.S. white husbands have the income less than 50K. Although people cannot address one specific person from the pattern, it is still very crucial to protect the equality of certain groups and avoid discrimination. Such as group with the same occupation, marriage status, country/region, working hours per week, sex, race and income etc. From our point of view, researchers, companies or other organizations can never publish these patterns even if they legally use them to make profits or to do some other non profit affairs.

The end of the report