

HW2 – Scene Recognition & Image Classification Using CNN

Computer Vision
NTU, Spring 2022

Announced: 03/25 2022(Fri.)

Due: 04/15 2022(Thur.) 23:59

Outline

- Part 1. Scene Recognition
 - Use **SIFT** in opencv as a feature extractor.
 - Apply **K-Nearest Neighbor Algorithm** as a weak classifier.
- Part 2. Image Classification
 - Use **convolutional neural network** as a feature extractor and perform image classification.

What You Will Learn

- Basics
 - What **the pipeline of bag of sifts** is. **Bag of Word**
 - How to build a **KNN classifier**.
 - Some useful function in opencv and cvlfeat.
 - How to build **convolutional layers, fully-connected layers and residual blocks in CNN-based model**.
 - How to train a model under **pytorch** framework.
- Advanced learning (optional) **加分**
 - How to perform simple **data augmentation method** in pytorch to gain accuracy.
 - How to perform **data cleaning method** on some dirty data.
 - How to supply **semi-supervised** to unlabeled data.

Preparation

- Before getting started, you have to download the dataset in the following link,
- Install pytorch package in official website. (strongly recommended)
 - [Start Locally | PyTorch](#) [1]

START LOCALLY

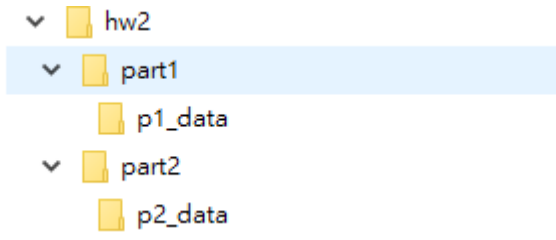
Select your preferences and run the install command. Stable represents the most currently tested and supported version of PyTorch. This should be suitable for many users. Preview is available if you want the latest, not fully tested and supported, 1.11 builds that are generated nightly. Please ensure that you have **met the prerequisites below (e.g., numpy)**, depending on your package manager. Anaconda is our recommended package manager since it installs all dependencies. You can also [install previous versions of PyTorch](#). Note that LibTorch is only available for C++.

Additional support or warranty for some PyTorch Stable and LTS binaries are available through the [PyTorch Enterprise Support Program](#).

PyTorch Build	Stable (1.11.0)	Preview (Nightly)	LTS (1.8.2)	
Your OS	Linux	Mac	Windows	
Package	Conda	Pip	LibTorch	Source
Language	Python		C++ / Java	
Compute Platform	CUDA 10.2	CUDA 11.3	ROCm 4.2 (beta)	CPU
Run this Command:	pip3 install torch torchvision torchaudio			

Preparation

- Extract hw2_data.zip. Move “p1_data” and “p2_data” in your working space as shown in the following directory.



- The download link for hw2_data.zip
 - https://drive.google.com/u/1/uc?id=1Uq1_00JtfZ8ETueo8RjPvL6ANhlc1qvD&export=download

Part 1. Scene Recognition

BoW Scene Recognition

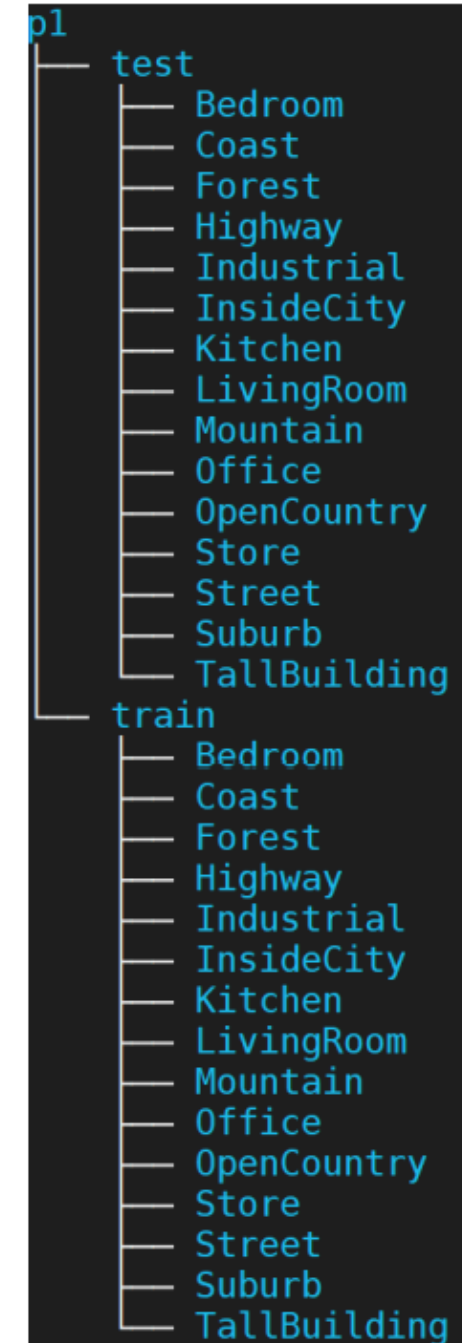
- Tiny images representation and nearest neighbor classifier.
- **Bag of SIFT** representation and nearest neighbor classifier.



Reference:[2] http://media.ee.ntu.edu.tw/courses/cv/21S/slides/cv2021_lec05.pdf , page 46-49

Dataset Description [3]

- hw2_data/p1/train
 - 100 images per category
- hw2_data/p1/test
 - 100+ images per category



Assignment Description

You will have the files....

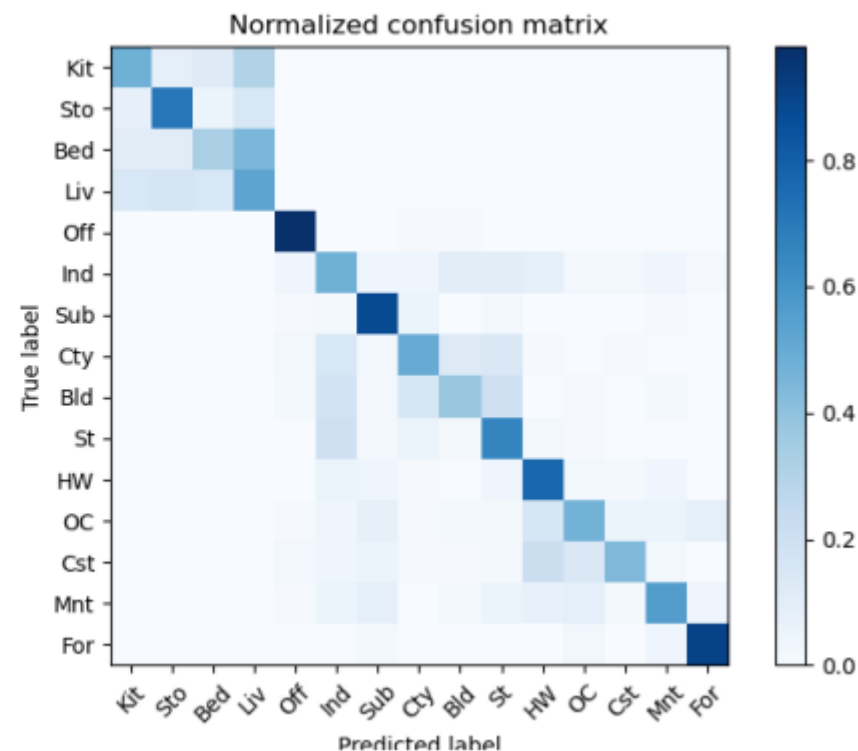
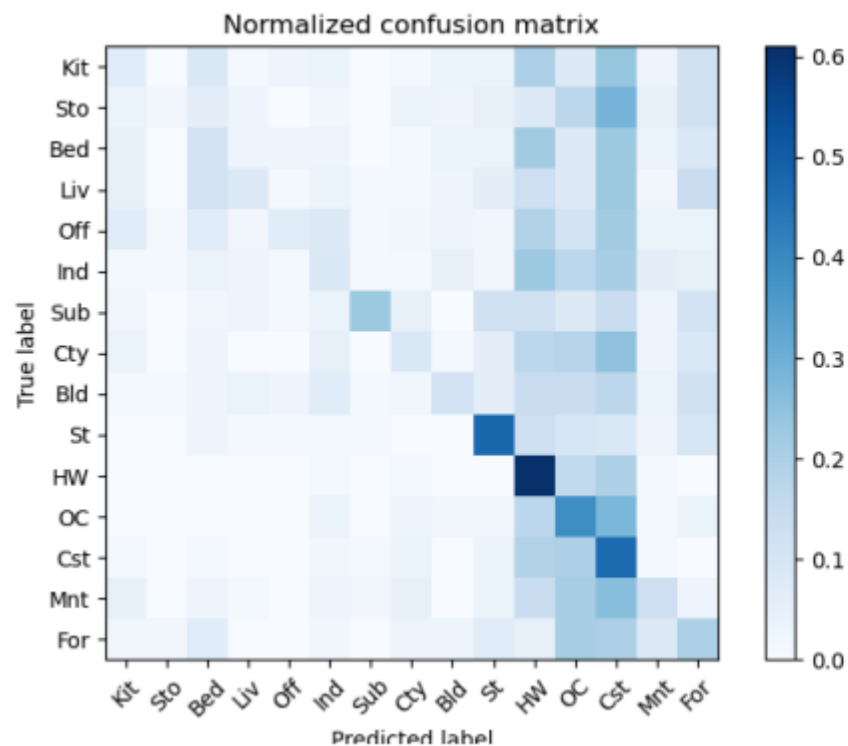
- part1/p1.py
 - Read image, construct feature representations, classify features, etc.
- part1/get_tiny_images.py **## TO DO ##**
 - Build tiny images features. **Resize進行分類**
- part1/build_vocabulary.py **## TO DO ##**
 - Sample SIFT descriptors from training images, cluster them with k-means and return centroids.
- part1/get_bags_of_sifts.py • **## TO DO ##**

Construct SIFT and build a histogram indicating how many times each centroid was used.
- part1/nearest_neighbor_classify.py **## TO DO ##**
 - Predict the category for each test image.
 - **CAN NOT** USE `sklearn.neighbors.KNeighborsClassifier`

Confusion Matrix

- Result visualization – confusion matrix

對角線越深，分類越好



Part 2. Image Classification

Task Description

- In this part, you need to build a CNN-based model to predict the labels for the certain images.



Ship, Cat, Ship, Dog, Dog,
Horse, Deer, Frog, Ship, Frog

Dataset Description

- Original Cifar-10 dataset [4] contains
 - 50,000 training images.
 - For each class it contains 5000 images
 - 10,000 test images.
- In the dataset, all images consists RGB channel with resolution equal to 32*32.

airplane



automobile



bird



cat



deer



dog



frog



horse



ship



truck



Dataset Description

- In the homework, we are using **Cifar-10 mini** given by TA
 - It contains only **23,000 images for training**.
 - In the training set, TA mixed up to **3000 dirty images** which may not belong to any of the class.
 - Besides, you will get extra **30,000 unlabeled** data for semi-supervised
 - TA will give you 5000 images as the public score for testing.
 - TA will evaluate another 5000 images as the private score.

Example for dirty images



Bird, Airplane, Deer, Frog, Bird
Dog, Horse, Deer, Ship, Truck

Assignment Description

You will have the files....

- part2/main.py
 - Top. Start training and some basics settings, etc.
- part2/cfg.py
 - Some hyperparameters, seeds setting for certain mode.
- part2/myDatasets.py
 - Define your customized Datasets for training process. **## TO DO ##**
- part2/tool.py **## TO DO ##**
 - Functions/tools for saving/loading model parameters, Training/validation process, and some other useful function.
- part2/myModels.py • **## TO DO ##**
 - Define your own modelzoo including at least myResnet and myLenet
- part2/eval.py
 - Predict the labels for public datasets. **## TO DO ##**
- Note : In part2. , **feel free to modify all the files as long as it's reasonable** and reproducible.

Pytorch
Notes

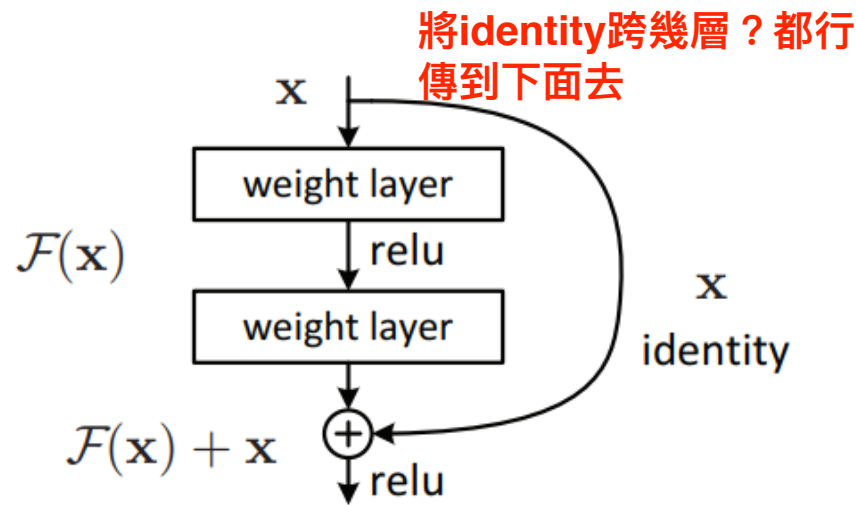
這個做完去執行
main.py

Basic Flows for Training a Model

1. Define your "cifar10_dataset" for data.
 - You can apply data augmentation in the stage. **define your dataset**
2. Define your objective function or loss function.
3. Train the model iteratively
 - Forward → **Calculate gradient → Backpropagation** **Pytorch framework 使用就好**
CNN or Classifier
4. Apply validation set in the case of overfitting.
 - Only apply forward path to check accuracy compared with the training process. **Compare your training with your test**
5. Apply the well-trained model on your test set.

Residual Block

- Build your own Resnet using the residual block.
- Residual block [5]
 - You can add extra layer yourself.



```
38 class residual_block(nn.Module):
39     def __init__(self, in_channels):
40         super(residual_block, self).__init__()
41
42         self.conv1 = nn.Sequential(nn.Conv2d(in_channels=in_channels, out_channels=in_channels, kernel_size=3, padding=1),
43                                     nn.BatchNorm2d(in_channels))
44
45         self.relu = nn.ReLU()
46
47     def forward(self, x):
48         ## TO DO ##
49         # Perform residual network.
50         # You can refer to our ppt to build the block. It's ok if you want to do much more complicated one.
51         # i.e. pass identity to final result before activation function
52         pass
53
54
55 class myResnet(nn.Module):
56     def __init__(self, in_channels=3, num_out=10):
57         super(myResnet, self).__init__()
58
59         self.stem_conv = nn.Conv2d(in_channels=in_channels, out_channels=64, kernel_size=3, padding=1)
60
61         ## TO DO ##
62         # Define your own residual network here.
63         # Note: You need to use the residual block you design. It can help you a lot in training.
64         # If you have no idea how to design a model, check myLeNet provided by TA above.
65
66         pass
67
68     def forward(self, x):
69         ## TO DO ##
70         # Define the data path yourself by using the network member you define.
71         # Note : It's important to print the shape before you flatten all of your nodes into fc layers.
72         # It help you to design your model a lot.
73         # x = x.flatten(x)
74         # print(x.shape)
75
76         pass
```

Data Augmentation

- CNN are not rotational-invariant !! We need to apply a serial of data augmentation to train a robust model.
- You can simply apply a built-in function in pytorch
 - <https://pytorch.org/vision/stable/transforms.html>

將transform套用即可

```
38     ## TO DO ##
39     # Define your own transform here
40     # It can strongly help you to perform data augmentation and gain performance
41     # ref: https://pytorch.org/vision/stable/transforms.html
42     means = [0.485, 0.456, 0.406]
43     stds = [0.229, 0.224, 0.225]
44     train_transform = transforms.Compose([
45         ## TO DO ##
46         # You can add some transforms here
47
48         transforms.ToTensor(),
49         transforms.Normalize(means, stds),
50     ])
```



Cleaning The Data

不要一開始就套用strong model

- You could apply a **weak model** to the original dataset.

- Discard the image with low confidence.
- Reserve the image with high confidence.

K mean or CNN

Ex. 10 centroids, if 10 are out of the plot, then delete it.

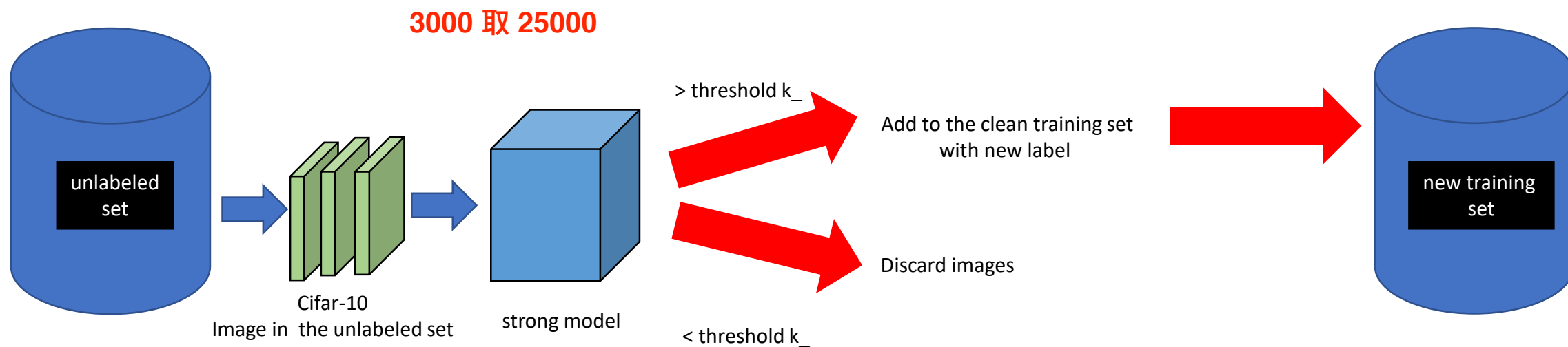
- You could also apply K-mean centroids algorithm.
 - Discard the images whose feature maps are far away from the centroid.



Semi-supervised Learning

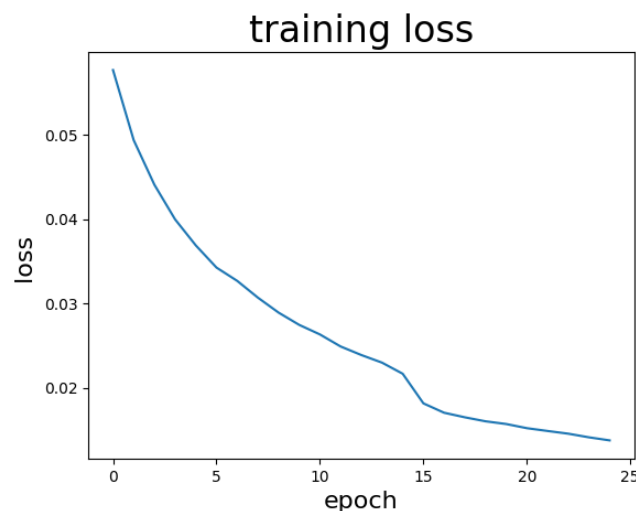
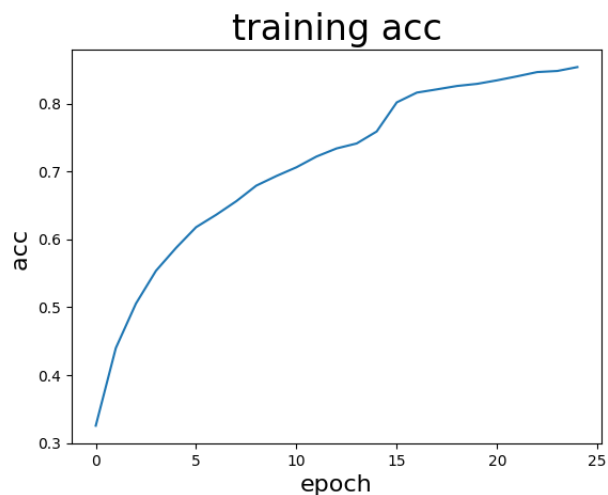
- Apply a well-trained model to verify if the images need to be preserved.

做完之後要增加新的過threshold照片進到training dataset



Plot Learning Curve

- Report your model's architecture and learning curve for both Lenet and resnet.



```
myResnet(
  (stem_conv): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (layer1): residual_block(
    (conv1): Sequential(
      (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (relu): ReLU()
  )
  (cnn_layer2): Sequential(
    (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (3): ReLU()
  )
  (layer3): residual_block(
    (conv1): Sequential(
      (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (relu): ReLU()
  )
  (cnn_layer4): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (3): ReLU()
  )
  (layer5): residual_block(
    (conv1): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (relu): ReLU()
  )
  (fc1): Sequential(
    (0): Linear(in_features=8192, out_features=512, bias=True)
    (1): ReLU()
  )
  (fc2): Linear(in_features=512, out_features=10, bias=True)
)
```

Submission and Some Notes

Execution of hw2

- TAs will run your codes as the following manner,
- Part 1.
 - `python3 p1.py $1 $2 $ 3`
 - \$1: type of feature representation (tiny images/SIFT)
 - \$2: type of classifier(nearest neighbor)
 - \$3: dataset path
 - E.g., `python3 p1.py -- feature tiny_images -- classifier nearest_neighbor -- dataset_path ./p1_data/`
- Part 2.
 - `python3 main.py` → It need **to generate your final result (.pt)** and **reproduce the accuracy** in your report.
 - `python3 eval.py $1 $2`
 - \$1 the path of model's parameter
 - \$2 the path of the annotation for test data
 - E.g.
 - `python3 eval.py --path ./save_dir/LeNet/best_model.pt --test_anno ./data/annotations/public_test_annos.json`

Submission

- Directory architecture:

- R07654321_hw2/

- / report.pdf

- /part1

- / p1.py, get_tiny_images.py, build_vocabulary.py, get_bags_of_sifts.py, nearest_neighbor_classify.py

- / vocab.pkl, train_image_feats.pkl, test_image_feats.pkl

- /part2 **Bag of Word**

- / ReadMe.MD → Write a simple read me to tell TA how to run your code. Important !!

- / train.py → **It needs to generate .pth** file, which is the final parameter of the model you use in your report.

- / eval.py → TA could simply run, " python3 eval.py " to utilize .pth file that train.py generated to evaluate your code on public dataset

- / myModel.py → To clearly show the model you build yourself.

- / any other file you need.

- Put all above files in a directory (StudentID_hw2, e.g. R07654321_hw2) and compress the directory into zip file **StudentID_hw2.zip (e.g. R07654321_hw2.zip)**

- **Note : You don't need to submit your model's parameter (.pt) or raw data !!!!!!!!**

- Submit to **NTU COOL**

- **Deadline: 11/04/13 (Thur.) 23:59**

- Late policy: http://media.ee.ntu.edu.tw/courses/cv/22S/hw/delay_policy.pdf

Rules

- You can only use the dataset TA provided. You are **not allowed to used original dataset online**.
- Pretrained model is allowed if and only if the model is pretrained on ImageNet. **No more pretrained weights are allowed.**
- TA will reproduce your training in part2. If you cannot match the accuracy in your report, TA will send you an e-mail to run another chance only for one time.
 - Note: Your code needs to be finished training in **12 hours** and your model size should less **than 100 MB**.
- Plagiarism is forbidden !
- If you violate the any of the rules above, you will get 0 point in the corresponding sections.

Grading

- Part 1 : 30 % + extra 5 %
 - Model Performance(25%)
 - Accuracy should be above the baseline score to get points
 - Tiny images + KNN(10%): **0.2**
 - Bag of SIFT + KNN (15%):
 - Weak baseline (9%): **0.55**
 - Strong baseline (6%): **0.6**
 - TAs will execute your code to check if you pass the baseline.
 - Report(10%)
 - Plot confusion matrix of two settings. (5%)
 - Compare the results/accuracy of both settings and explain the result. (5%)

Grading

- Part 2 : 70 % + extra 5 %
 - Model Performance(40%)
 - TA will test your code on both private and public test sets.
 - Weak baseline : accuracy > **64.65%**. Both 5 % for the private and public test sets (10%)
 - Medium baseline : accuracy > **72.30%**. Both 7.5 % for the private and public test sets (15%)
 - Strong baseline : accuracy > **77.92%**. Both 7.5% for the private and public test sets (15%)
 - Report(35%)
 - Compare the performance on **residual networks and LeNet**. Plot the learning curve (loss and accuracy) on both training and validation sets for both 2 schemes. 8 plots in total. (20%)
 - Attach basic information of the model you use including **model architecture and number of the parameters**. (5%)
 - Briefly describe what method do you apply ? (e.g. data augmentation, model architecture, loss function, etc.)(10%)

Packages TA used

- python: 3.6+
- numpy: 1.19.2+
- cv2feat: 0.5.1+
- matplotlib: 3.3.4+
- pillow: 8.1.2+
- scipy: 1.5.2+
- opencv-python: 4.5.1+
- sklearn: 0.24.1+
- pytorch: 1.5.1+ (<https://pytorch.org/get-started/locally/>)
- torchvision: 0.6.1+
- And other standard python packages
- E-mail or ask TA first if you want to import other packages.

If You Have Problems...

- **Use NTU cool** (strongly recommended)
 - TA will answer the questions every day and record some common problems you may face.
 - https://cool.ntu.edu.tw/courses/14814/discussion_topics/94504
- Attach TA
 - E-main: mjsun@media.ee.ntu.edu.tw
 - Office hour in the lab or online TA hour
- Goooooooooooooogle yourself.

TA information

- Ming-Jhih Sun (孫名志)

E-mail: mjsun@media.ee.ntu.edu.tw

TA hour: Wed. 10:00 - 12:00

Location: 博理 421

Online TA hour : Every Mon. & Thur. 20:00 – 21:00 during the period of hw2

<https://meet.google.com/txc-ppsa-sai>

Note: Send an e-mail including your problems if you want to attend online TA hour !!

- Chih-Ting Liu (劉致廷)

E-mail: jackieliu@media.ee.ntu.edu.tw

Location: 博理 421

Supplementary

Tips for Achieving the Baselines

- In Part 1.
 - Consider different metrics to evaluate the distance between features.
 - Ref: [scipy.spatial.distance.cdist — SciPy v1.8.0 Manual](#) [6]
- In part 2.
 - Weak baseline – **a simple residual model** + little effort
 - Medium baseline – **data augmentation + adjusting learning rate**
(+add some batchnorm and pooling layers)
 - Strong baseline – **a stronger model + data augmentation + data cleaning** + semi-supervised + **adjusting learning rate** +add some **batchnorm and pooling layers**

TA's Experience for Part 2.

- TA trained the model by CPU only.
 - TA's equipments : Intel(R) Core(TM) **i9-9900K CPU** @ 3.60GHz + 128 GB RAM
- The model TA applied.
 - TA applied a super shallow model with only 2 residual blocks without any pretrained weight.
 - The size of the parameter is approximately 17 MB only.
- Training milestones
 - For each epoch with 23,000 images, it takes ~ **4 mins.**
 - TA runs total 25 epochs to get the performance by **73.1%**
 - With another 25 epochs for data cleaning, TA get the performance by **77.3%.**
 - Semi-supervised is applied and TA trained **48,262 images** in total.
 - For each epoch, it takes ~ 8 min. With total 25 epochs, TA get the performance by **79.54%.**

epoch_5.pt	17 731	2022-03-24 17:13
epoch_4.pt	17 731	2022-03-24 17:13
epoch_3.pt	17 731	2022-03-24 17:13
epoch_2.pt	17 731	2022-03-24 17:13
epoch_1.pt	17 731	2022-03-24 17:12
epoch_0.pt	17 731	2022-03-24 17:12

For Pytorch & Colab Tutorial

- For Pytorch & colab tutorial
 - [7] Machine Learning Couse. Prof. Lee-HY Website [ML 2022 Spring \(ntu.edu.tw\)](http://ml2022spring.ntu.edu.tw)
 - colab tutorial
 - <https://www.youtube.com/watch?v=YmPF0jrWn6Y>
 - <https://speech.ee.ntu.edu.tw/~hylee/ml/ml2022-course-data/Colab%20Tutorial%202022.pdf>
 - Pyortch tutorial 1
 - <https://www.youtube.com/watch?v=85uJ9hSaXig>
 - <https://speech.ee.ntu.edu.tw/~hylee/ml/ml2022-course-data/Pytorch%20Tutorial%201.pdf>
 - Pytorch tutorial 2
 - <https://www.youtube.com/watch?v=VbqNn20FoHM>
 - <https://speech.ee.ntu.edu.tw/~hylee/ml/ml2022-course-data/Pytorch%20Tutorial%202.pdf>

Reference

- [1] Pytorch download. <https://pytorch.org/get-started/locally/>
- [2] Introduction to BoW. http://media.ee.ntu.edu.tw/courses/cv/21S/slides/cv2021_lec05.pdf
- [3] Scence Recognition datasets. S. Lazebnik, C. Schmid, and J. Ponce, "Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories," CVPR, 2006
- [4] Cifar 10 Datasets [Learning Multiple Layers of Features from Tiny Images](#), Alex Krizhevsky, 2009. [CIFAR-10 and CIFAR-100 datasets \(toronto.edu\)](#).

Reference

- [5] Deep Residual Learning for Image Recognition. K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90
- [6] [scipy.spatial.distance.cdist — SciPy v1.8.0 Manual](#)
- [7] Pytorch & Colab tutorial [ML 2022 Spring \(ntu.edu.tw\)](#)