# ML2023 Spring HW3 - CNN

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### Outline

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- Dataset
- Evaluation Metrics
- Kaggle Submission
- Gradescope
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# **Task Introduction - Image Classification**

• Solve image classification with **convolutional neural networks(CNN)**.





#### Dataset

- The images are collected from the food-11 dataset splitted into 11 classes.
- Training set: 10000 labeled images
- Validation set: 3643 labeled images
- Testing set: 3000 images without labeled

#### **Evaluation Metrics**

• Accuracy on testing set

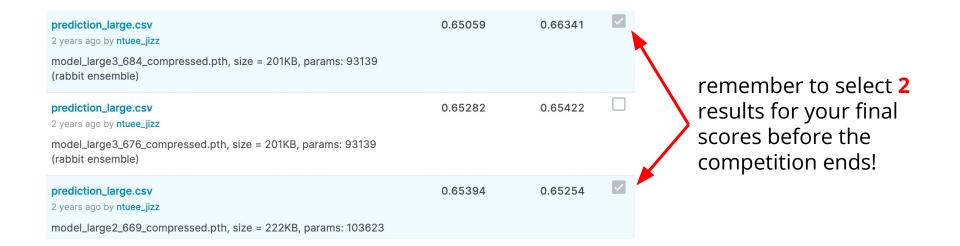
$$\mathrm{Acc} = rac{\mathrm{pred} == \mathrm{label}}{len(\mathrm{data})} \cdot 100\%$$

# Kaggle Submission (1 / 3) - Links

- Display name: <student ID>\_<anything>
  - e.g. b10901666\_MLmaster
  - For auditing, don't put student ID in your display name.
- <u>Kaggle links</u>
- HW Deadline: 2023/3/31 23:59 (UTC+8)

# Kaggle Submission (2 / 3) - Rules

- You may submit up to **5** results each day (UTC+8, AM 8:00)
- Up to **2** submissions will be considered for the private leaderboard



# Kaggle Submission (3 / 3) - Format

• The file should contain a header and have the following format:

Id,Category 0000,1

- Id corresponds to the jpg file name in test.
- Follow the sample code if you have trouble with formatting.

# Gradescope

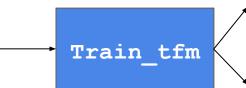
- Gradescope links
- Submit with gradescope, no need to upload any files.
- We can only see your last submission.
- Gradescope deadline: 2023/3/31 23:59 (UTC+8)

# Q1. Augmentation Implementation (2%)

Implement augmentation by finishing train\_tfm in the code with image size of your choice. Copy your train\_tfm code and paste it onto the GradeScope, and explain the effects of transformations you report.

- Your train\_tfm must be capable of producing 5+ different results when given an identical image multiple times.
- Your train\_tfm in the report can be different from train\_tfm in your training code.











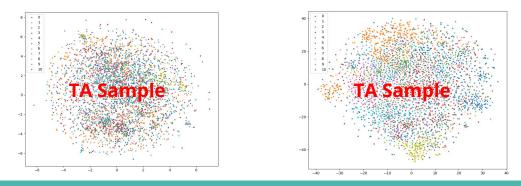






# **Q2. Visual Representations Implementation (2%)**

- Visualize the learned visual representations of the CNN model on the validation set by implementing t-SNE (t-distributed Stochastic Neighbor Embedding) on the output of both top & mid layers (You need to submit 2 images).
- Briefly explain your result of the t-SNE visualization.



# Q2. Visual Representations Implementation (2%)

- Take the CNN architecture beside as example.
- The layers contained within the red box may be identified as the "Bottom layers."
- The layers contained within the green box may be identified as the "Mid layers."
- The layers contained within the blue box may be identified as the "Top layers."

sel	f.cnn = nn.Sequential(
	nn.Conv2d(3, 64, 3, 1, 1), # [64, 128, 128]
	nn.BatchNorm2d(64),
	nn.ReLU(),
	nn.MaxPool2d(2, 2, 0), # [64, 64, 64]
	nn.Conv2d(64, 128, 3, 1, 1), # [128, 64, 64]
	<pre>nn.BatchNorm2d(128),</pre>
	nn.ReLU(),
l	nn.MaxPool2d(2, 2, 0), # [128, 32, 32]
	<pre>nn.Conv2d(128, 256, 3, 1, 1), # [256, 32, 32] nn.BatchNorm2d(256), nn.ReLU(),</pre>
	nn.MaxPool2d(2, 2, 0), # [256, 16, 16]
ſ	nn.Conv2d(256, 512, 3, 1, 1), # [512, 16, 16]
	nn.BatchNorm2d(512),
	nn.ReLU(),
	nn.MaxPool2d(2, 2, 0), # [512, 8, 8]
	nn.Conv2d(512, 512, 3, 1, 1), # [512, 8, 8]
	<pre>nn.BatchNorm2d(512),</pre>
	nn.ReLU(),
	nn.MaxPool2d(2, 2, 0), # [512, 4, 4]

### **Code Submission**

• Compress your code, then submit it to NTU COOL.

<student ID>\_hw3.zip

e.g. b10901666\_hw3.zip

- If your codes are complicated, please write a README file.
- We can only see your last submission.
- Do not submit your model or dataset.
- If your code is not reasonable, your final grade will be multiplied by 0.9!
- Submission deadline:
  - o 2023/3/31 23:59 (UTC+8)

# Grading Policy - Baseline (1 / 2)

Baseline	Accuracy	Hints	Training Time (Reference)
Simple	0.637	Run Sample Code	0.5hr - 1hr on Colab
Medium	0.700	Do some Data Augmentation & Train longer	1.5hr - 2hr on Colab
Strong	0.814	Use predefined CNN from torchvision or TensorFlow	10hr - 12hr on Colab (Suggest using Kaggle)
Boss	0.874	Cross Validation + Ensemble or any other methods you know	40+hr on Kaggle

# Grading Policy - HW Score (2 / 2)

(private)

(public)

(public)

(private)

(public)

(private)

- simple
- simple
- medium
- medium
- strong
- strong
- boss
- (public) (private) boss
- code submission
- report

+0.5 pts +2 pts +4 pts Total: 10 pts

# Regulations

- You should **NOT** plagiarize, if you use any other resource, you should cite it in the reference. ( \* ) <u>Academic Ethics Guidelines for Researchers by the Ministry of Science and Technology</u>
- You should **NOT** modify your prediction files manually.
- Do NOT share codes, checkpoints, and prediction files with any living creatures.
- Do NOT use any approaches to submit your results more than 5 times per day.
- Do NOT use additional data (including finding the answers of testing set) and any pre-trained model.
- Your **assignment will not be graded** and your **final grade x 0.9** if you violate any of the above rules.
- Prof. Lee & TAs preserve the rights to change the rules & grades.

# **Hints for baseline**

# **Data Augmentation**

- Modify the image data so non-identical inputs are given to the model each epoch, to prevent overfitting of the model
- Visit <u>torchvision.transforms</u> for a list of choices and their corresponding effect. Diversity is encouraged! Usually, stacking multiple transformations leads to better results.
- Coding:fill in train\_tfm to gain this effect



# **Model Selection**

- Visit <u>torchvision.models</u> for a list of model structures, or go to <u>timm</u> for the latest model structures.
- Pretrained weights are not allowed.
  - Torchvision before 0.13 -> pretrained=False
  - After 0.13 -> weights=False

#### Classification

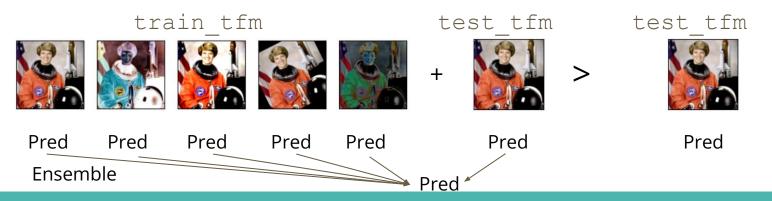
The models subpackage contains definitions for the following model architectures for image classification:

- AlexNet
- VGG
- ResNet
- SqueezeNet

Pre-defined model

#### **Test Time Augmentation**

- The sample code tests images using a deterministic "test transformation"
- You may using the train transformation for a more diversified representation of the images, and predict with multiple variants of the test images.
- Coding: You need to fill in train\_tfm, change the augmentation method for test\_dataset, and modify prediction code to gain this effect



#### **Test Time Augmentation**

Usually, test\_tfm will produce images that are more identifiable, so you can assign a larger weight to test\_tfm results for better performance.

train tfm test tfm Pred Pred Pred Pred Pred

avg\_train\_tfm\_pred

test tfm pred

Ex : Final Prediction = avg\_train\_tfm\_pred \* 0.2 + test\_tfm\_pred\* 0.8 

# A sample procedure for beating the boss baseline

• The boss baseline might not be beaten with a single model trained on kaggle for 12hrs

Prediction

Train: 12h

• Your procedure can be ensemble of multiple models with parallelization



#### **Cross Validation**

- Cross-validation is a resampling method that uses different portions of the data to validate and train a model on different iterations. Ensembling multiple results lead to better performance.
- Coding : You need to merge the current train and validation paths, and resample form those to form new train and validation sets.



#### Ensemble

- Average of logits or probability : Need to save verbose output, less ambiguous
- Voting : Easier to implement
- Coding : basic math operations with numpy or torch

# **Experimental Tips**

- Augmentation is a must to prevent overfitting. A good augmentation can carry on to the testing phase with **Test Time Augmentation**.
- If you build your own network structure and have implemented augmentation, don't be afraid to scale up your model. (Many predefined models structure are huge and perform great)
- In TA's experiment, model structures with **subsampling (max pooling)** work better, simply choosing the best performing models on ImageNet according to websites is not always a good idea because pretrained weights are not allowed.

#### Other tricks.....

- on Classification
  - Label Smoothing Cross Entropy Loss
- on Optimization
  - Dropout
  - <u>BatchNorm</u>
  - Gradient Accumulation

# **Useful Links**

- <u>Course Website</u>
- <u>NTU COOL</u>
- <u>Kaggle Competition</u>
- <u>Gradescope</u>
- Sample Code (<u>Colab</u>)
- Sample Code (<u>Kaggle</u>)
- Video Links
  - Introduction to CNN
  - <u>tSNE</u>
- Pytorch Documentation
  - <u>torchvision.models</u>
  - <u>torchvision.transforms</u>

#### Deadline

- Kaggle Contest
  - o 2023/3/31 23:59 (UTC+8)
- GradeScope
  - o 2023/3/31 23:59 (UTC+8)
- Code Submission to NTU COOL
  - o 2023/3/31 23:59 (UTC+8)

# **Common Questions**

- About Submission
  - You should submit a code that produces one of your best results on Kaggle,.
  - You should compress the folder containing your codes into <student\_id>\_hw3.zip. If your filename is wrong, there would be a penalty on your hw3 score.
- About Kaggle
  - You should rename your display name on Kaggle by changing "Team name".
- About GradeScope
  - You should answer the questions on GradeScope, and no file about answer have to be submitted to NTU COOL.
- These would be updated on NTU COOL, please read the FAQ before you ask questions.

# If you have any questions, you can ask us via...

- Please see the FAQ before you ask questions!!!!!
- NTU COOL (recommended)
  - https://cool.ntu.edu.tw/courses/24108/discussion\_topics/184307
- Email
  - <u>mlta-2023-spring@googlegroups.com</u>
  - The title should begin with "[hw3]"
- TA hour
  - <u>meet.google.com/dzv-ppjx-qtq</u>
    - Monday 19:00 20:00 (中文)
    - Monday 20:00 21:00 (English)
  - Friday 上課課餘時間