PyTorch Seminar

Day2. CIFAR10 dataset training (2)

Duhyeon Kim / May 2025

PyTorch

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Contents

Things needed to Train CIFAR10

A. Neural Network Composition

B. CIFAR10 dataset

C. Custom Dataloader (role of transform function)

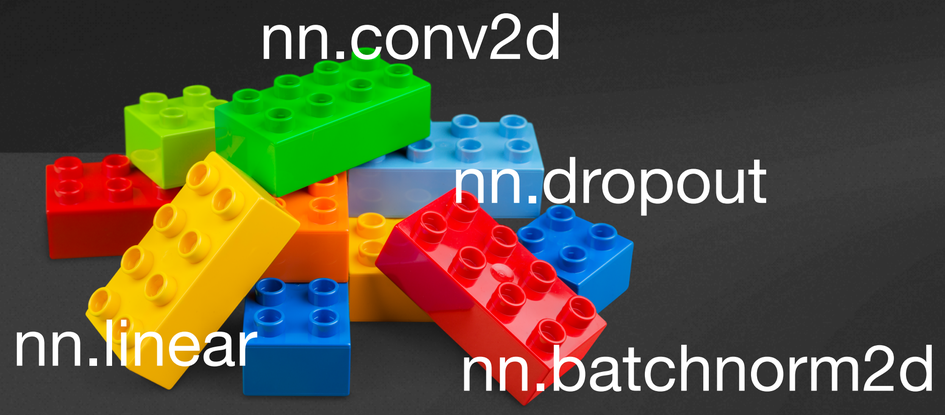
D. Custom Model (what is import ~ ?)

PyTorch

PyTorch nn composition

nn.Module

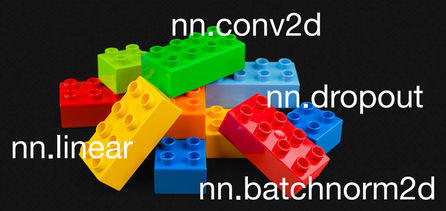
```
import torch.nn as nn
```



```
class CustomModel(nn.Module):
```

PyTorch nn composition

nn.Module

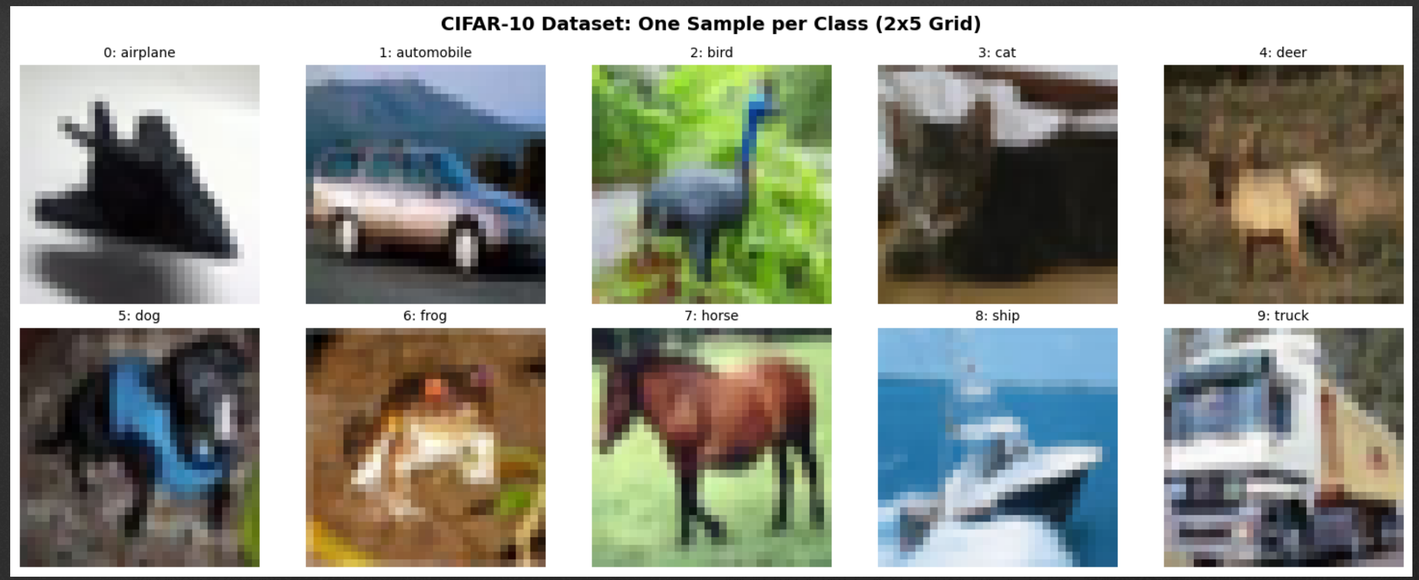


https://colab.research.google.com/drive/16tkCZEnTU0bhtTvB0vBppk6TrO7IC47k?usp=sharing

CIFAR-10 dataset

Overview

- 10 classes
  {'airplane': 0,’automobile': 1, 'bird': 2, 'cat': 3, 'deer': 4, 'dog': 5, 'frog': 6, 'horse': 7, 'ship': 8, 'truck': 9}
- 32x32 RGB images
- Train 50000 + Test 10000

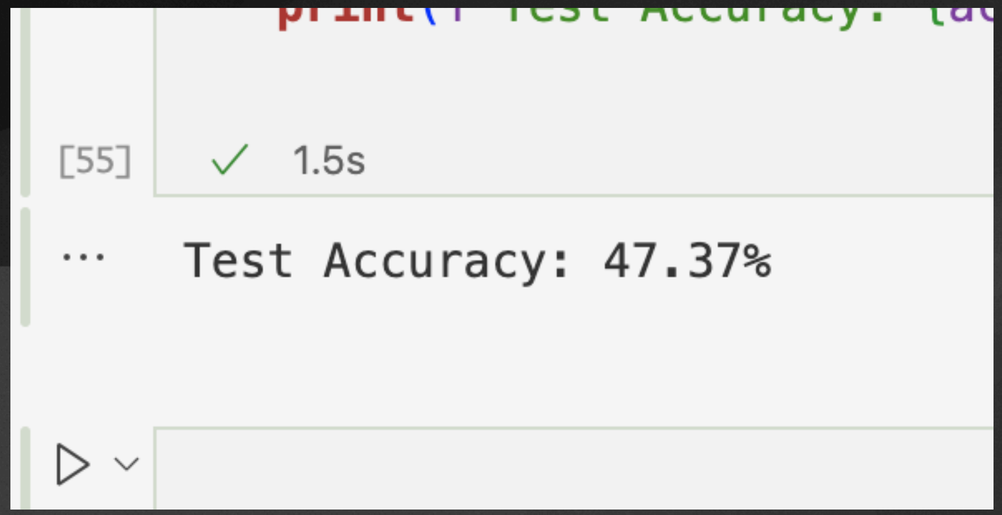


https://www.cs.toronto.edu/~kriz/cifar.html

Simplest CIFAR-10 Training

Simplest CIFAR-10 Training

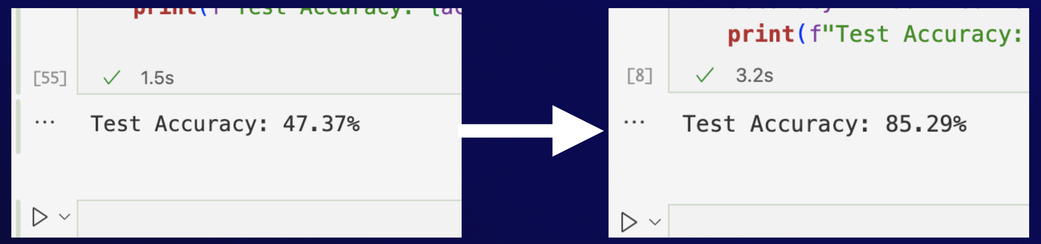
Evaluation Accuracy



47% > 10% (random sampling)

How to further **improve** Model Performance?

Model Improvement Techniques



Model Improvement Techniques

Roads to 100% accur.

A. Deeper Model

B. Data Augmentation (torchvision.transform)

C. Optimizer

D. When it comes to LLM (Deepseek)

Deeper Model

AlexNet (Krizhevsky et al., 2012)

ImageNet Classification with Deep Convolutional Neural Networks

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Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

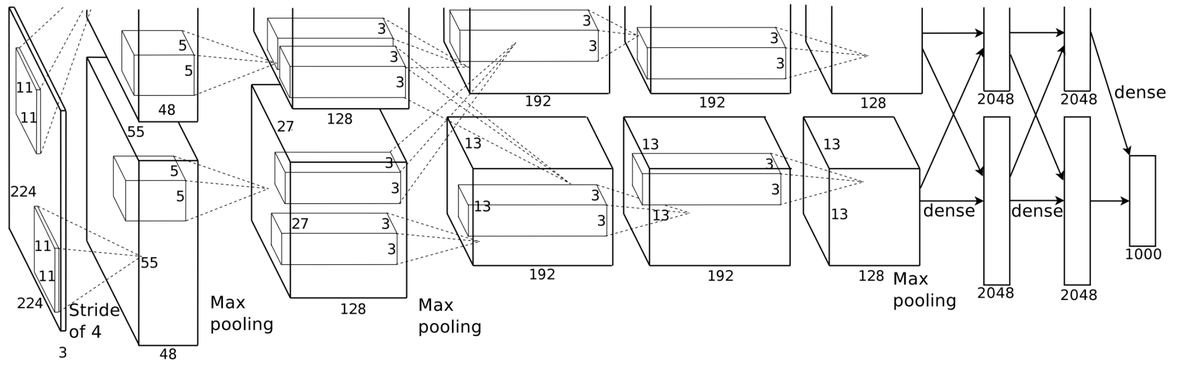
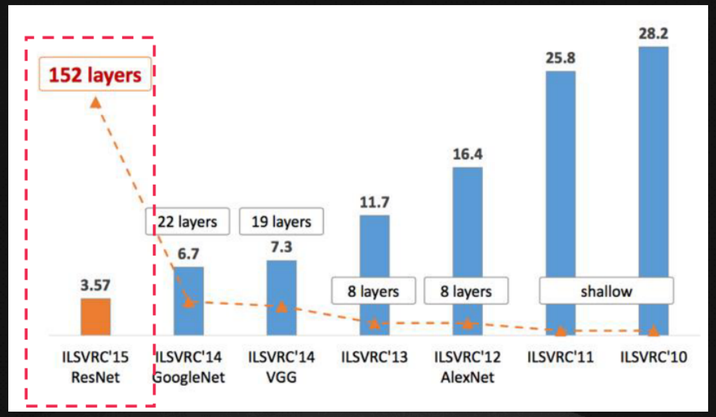


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

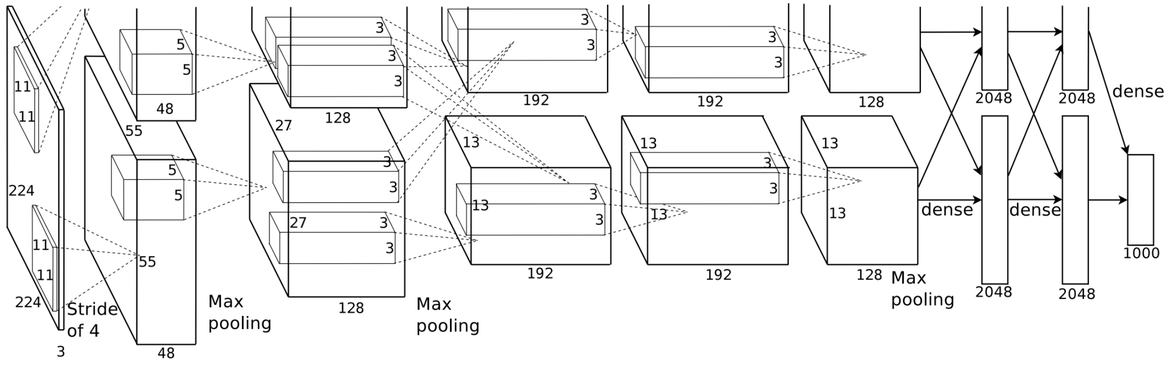
Deeper Model

AlexNet (Krizhevsky et al., 2012)



Key Milestones

- **DEEP** Convolutional Network
  - 5 (conv) + 3 (FC)
- ReLU activation
  - Training Speed up (6x)
  - Gradient Vanishing solved
- GPU in practice
  - DEEP -> GPU



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https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

Data Augmentation

torchvision.transforms

Meaning
& Effect of
Augmenting Data

- increase dataset size and diversity
- Overfitting Prevention
  - sees diff view of the same image
- Data Efficiency
  - one datum -> several data

Performance Boost

https://docs.pytorch.org/vision/0.9/transforms.html

Data Augmentation

torchvision.transforms

TORCHVISION.TRANSFORMS

Transforms are common image transformations. They can be chained together using `Compose`. Additionally, there is the `torchvision.transforms.functional` module. Functional transforms give fine-grained control over the transformations. This is useful if you have to build a more complex transformation pipeline (e.g. in the case of segmentation tasks).

All transformations accept PIL Image, Tensor Image or batch of Tensor Images as input. Tensor Image is a tensor with `(C, H, W)` shape, where `C` is a number of channels, `H` and `W` are image height and width. Batch of Tensor Images is a tensor of `(B, C, H, W)` shape, where `B` is a number of images in the batch. Deterministic or random transformations applied on the batch of Tensor Images identically transform all the images of the batch.

```python
# MODIFIED: Enhanced data augmentation techniques and added normalization
train_transform = transforms.Compose([
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomCrop(32, padding=4),  # MODIFIED: Added random crop
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010))
])
```

Transforms on torch.*Tensor only

PIL image

transforms.Compose

RandomHorizontalFlip

RandomCrop

ToTensor

Normalize

Tensor image

Transform is used in dataset __getitem__

https://docs.pytorch.org/vision/0.9/transforms.html

Optimizer

SGD to Adam

Stochastic Gradient Descent

$$\theta_t + 1 = \theta_t - \eta \nabla L(\theta t; x, y)$$

or

$$v_{t+1} = \beta v_t + \eta \nabla L(\theta_t; x, y)$$

$$\theta_{t+1} = \theta_t - v_{t+1}$$

Adaptive Moment Estimation

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla L(\theta_{t-1})$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)(\nabla L(\theta_{t-1}))^2$$

Momentum
Velocity

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_t = \theta_{t-1} - \frac{\eta \hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Carefully and meaningfully update Model Parameter

Custom Model

Computer Vision

- Residual Network https://arxiv.org/abs/1512.03385
- 3x3 kernel https://arxiv.org/abs/1409.1556
- Generator and Discriminator https://arxiv.org/abs/1406.2661
- VAE https://arxiv.org/abs/1312.6114
- Feature Fushion https://openaccess.thecvf.com/content/WACV2021/papers/Dai_Attentional_Feature_Fusion_WACV_2021_paper.pdf

Custom Model

LLM (transformers)

- Multi-Head Attention
- Multi-Head latent Attention
- Multi-Query Attention
- Group-Query Attention

Memory + Inference Speed

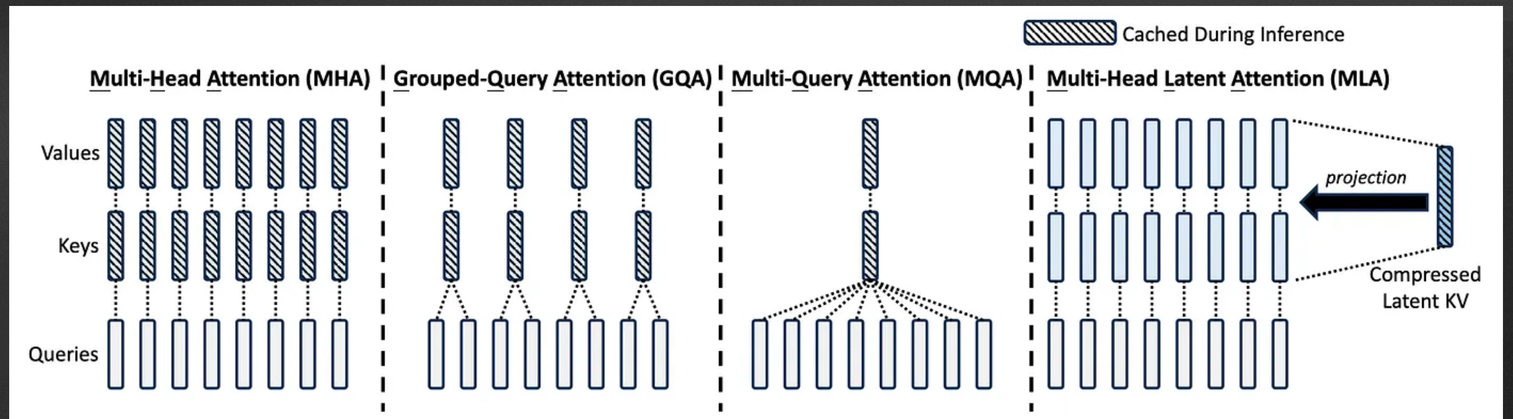

Figure 3 | Simplified illustration of Multi-Head Attention (MHA), Grouped-Query Attention (GQA), Multi-Query Attention (MQA), and Multi-head Latent Attention (MLA). Through jointly compressing the keys and values into a latent vector, MLA significantly reduces the KV cache during inference.

https://arxiv.org/pdf/2405.04434

Model Improvement Techniques in Code

Assignment #1

Your own dataset training

Dataset Search

https://datasetsearch.research.google.com/

https://www.kaggle.com/datasets

https://paperswithcode.com/datasets

kaggle

Assignment #1

Your own dataset training

Submit a Jupyter Notebook(.ipynb) that demonstrates:

✅ **Step 1: Custom Model Declaration**
Define your custom model class with proper architecture initialization and forward pass implementation.

📦 Step 2: Checkpoint Loading
Load the saved model weights from your checkpoint file into the custom model instance.

📊 Step 3: Dataset & Evaluation
Load the specified dataset and perform model evaluation to demonstrate the trained model's performance.

Thank you

Summary

Overall Code Structure

CNN

MLP

1 2 3 4 5 6 7 8 9 0

Predicted

```
{
    'cab': 0.08239,
    'dog': 0.04366,
    'cat': 0.09582,
    'car': 0.22994,
    'bird': 0.03967,
    'plane': 0.03967,
    'boat': 0.24323,
    'tree': 0.10801,
    'horse': 0.03135,
    'bike': 0.08626
}
```

Answer

```
{
    'cab': 1,
    'dog': 0,
    'cat': 0,
    'car': 0,
    'bird': 0,
    'plane': 0,
    'boat': 0,
    'tree': 0,
    'horse': 0,
    'bike': 0
}
```

Dataloader

CustomDataset

batches

Cross Entropy Loss

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

$$y_j = 1, \quad y_{i \neq j} = 0$$

$$L = -\log(\hat{y}_j)$$

SGD optimizer

$$\theta_{new} = \theta_{old} - \eta \cdot \nabla_\theta \cdot lr$$