

Assignment 2

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<http://data.snu.ac.kr>

Computer vision tasks

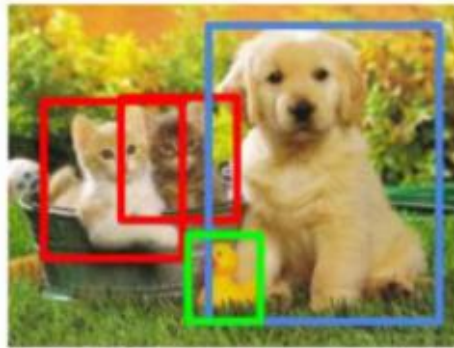
Classification



CAT

(Assignment 2-1)

Object Detection



CAT, DOG, DUCK

Instance Segmentation



CAT, DOG, DUCK

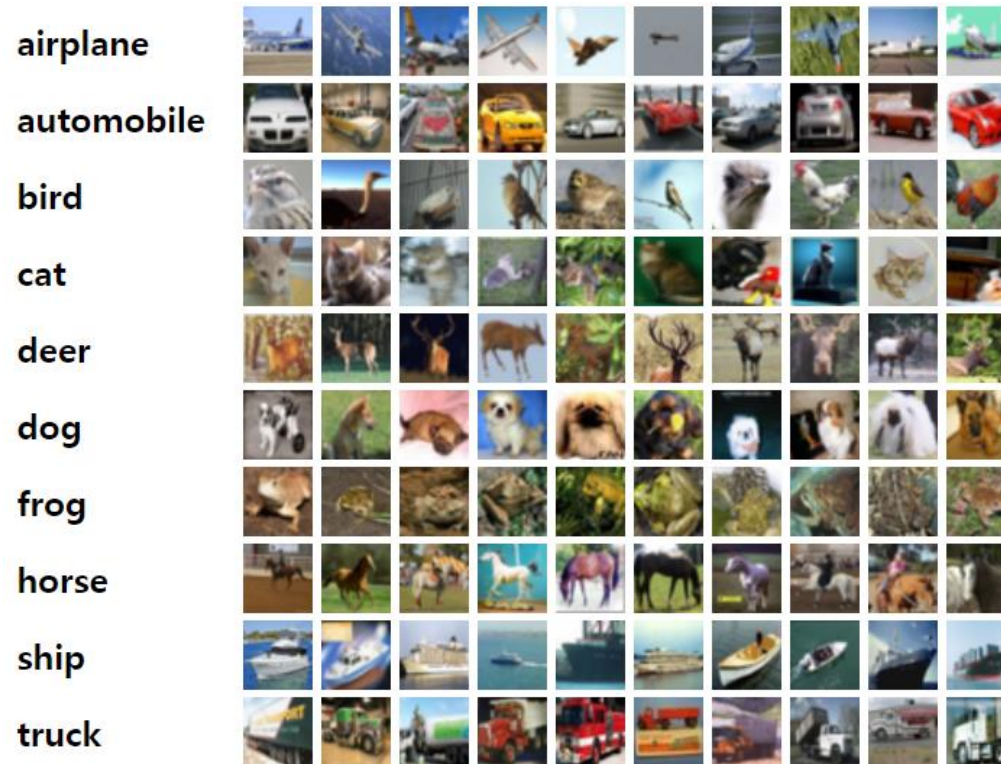
(Assignment 2-2)

- Besides, image reconstruction, image synthesis, style transfer, etc...

Assignment_2-1 Objective (Image classification)

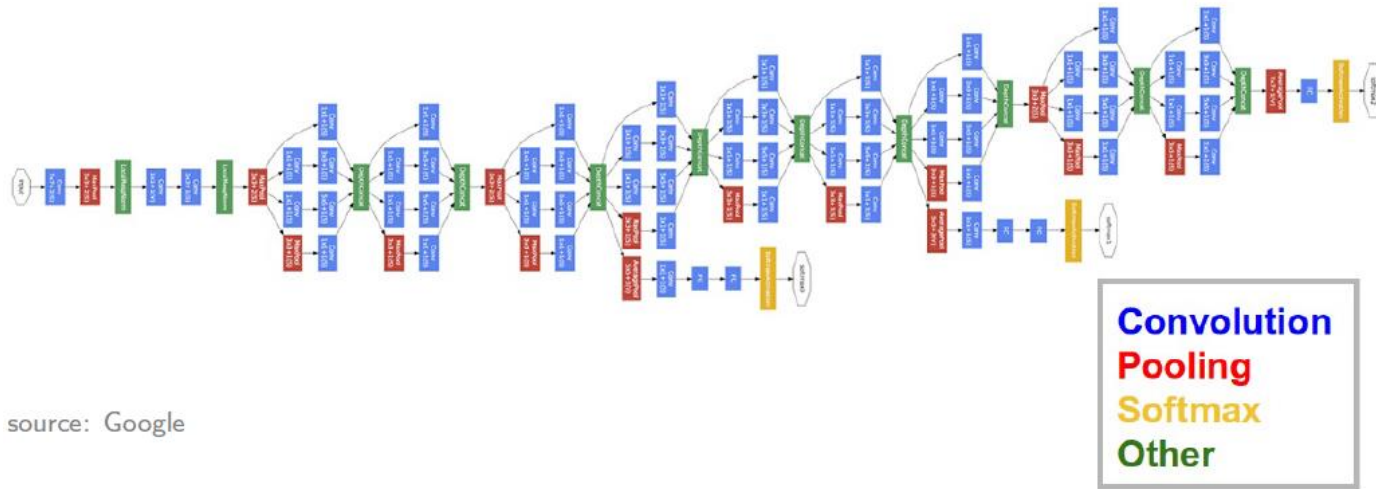
- Problem 1: Simple CNN model training on CIFAR-10 dataset
 - 문제에서 제시한 모델 그대로 구현
- Problem 2: Inception module 구현
 - 문제에서 제시한 모델 그대로 구현
 - Hyper parameter 변경 가능 (e.g. filter 수)
- Problem 3: Inception module을 활용한 CNN model training (CIFAR-10)
 - Test set accuracy $\geq 70\%$
 - Test set accuracy 상위 30% 가산점 부여
 - 구현한 모델 설명

CIFAR-10 dataset



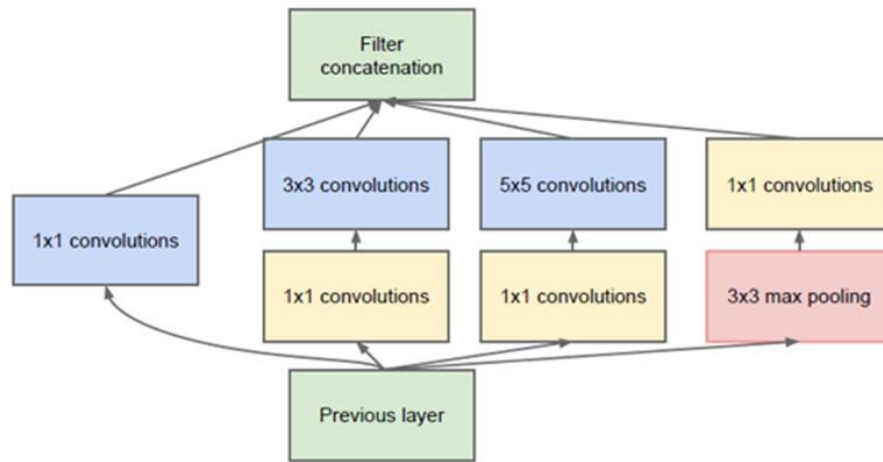
- Collection of images used to train machine learning and computer vision algorithms
- Consists of 60,000 32x32 color images in 10 classes, with 6,000 images per class
- There are 50,000 training images and 10,000 test images.
- The classes are completely mutually exclusive(no overlap between truck & automobile).

Inception model (a.k.a GoogLeNet)

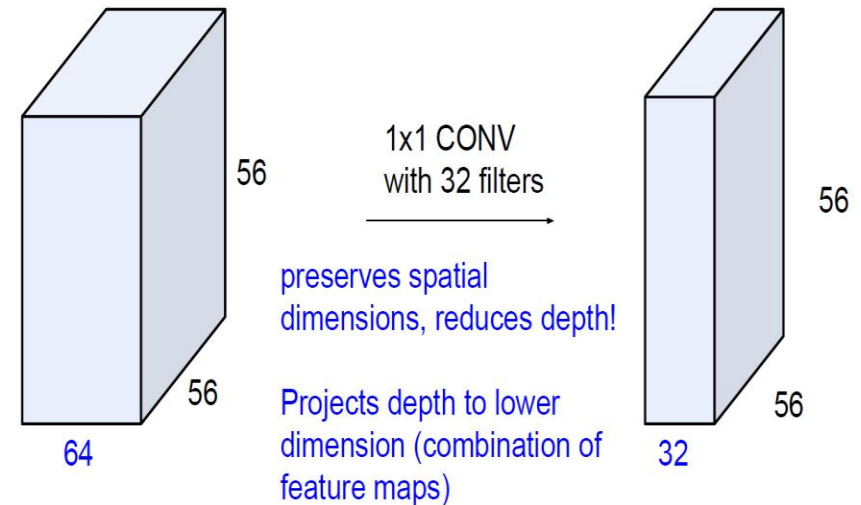


- Deeper network with computational efficiency
 - ImageNet Large Scale Visual Recognition Competition (ILSVRC) 2014 winner (6.7% top 5 error)
 - 22 layers with 5 million parameters (12x less than AlexNet *ILSVRC 2012 winner)
 - Efficient “Inception” module

Inception module



Inception module



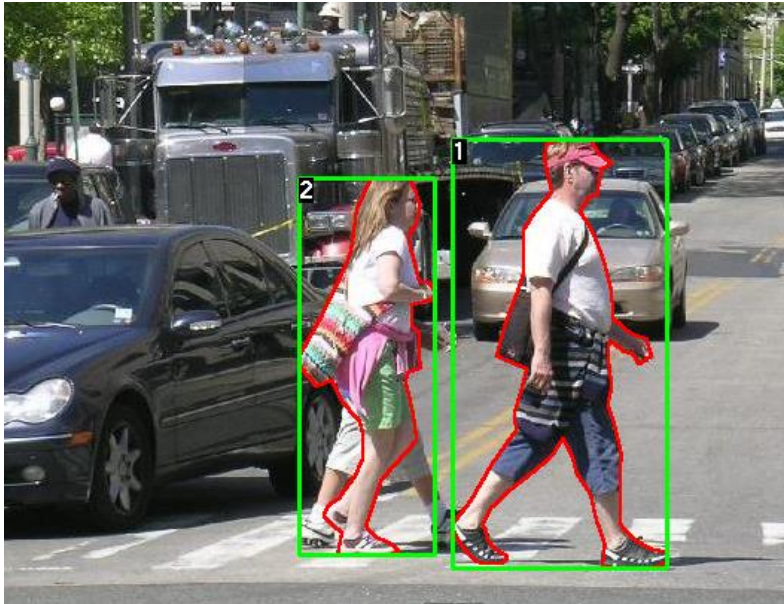
1x1 convolution

- Local network topology composing the Inception model
 - Apply parallel filter operations on the input from previous layer
 - Multiple filter sizes for convolution (1x1, 3x3, 5x5)
 - 1x1 convolution for dimensionality reduction

Assignment_2-2 Objective (Image segmentation)

- Problem 1: Finetuning model의 code 구현
 - 정의된 dataset과 pre-trained된 모델 활용하여 finetuning 코드 구현
 - 문제에서 제시한 4가지 구현
 - 예측된 segmentation mask(결과값) visualization
 - 구현한 코드 설명

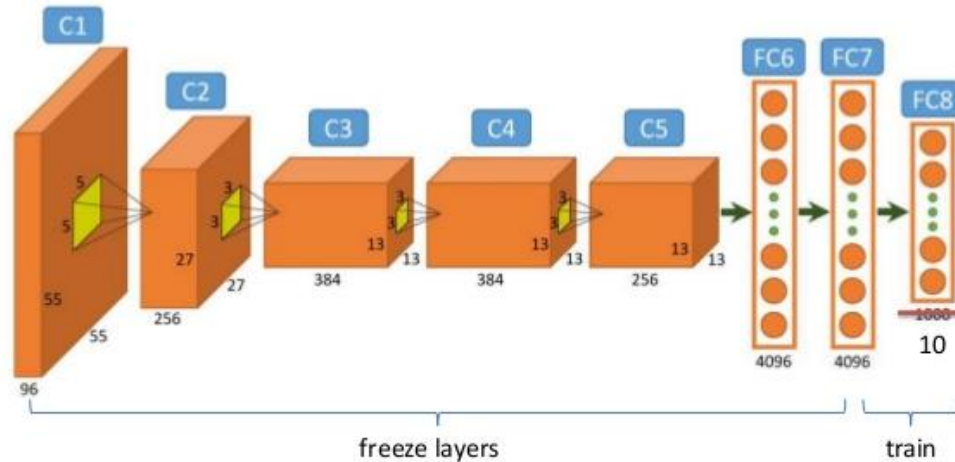
Penn-Fudan dataset



- Image dataset used for pedestrian detection and segmentation
- Consists of 170 images with 345 labeled pedestrians
- The heights of labeled pedestrians fall into $[180, 390]$ pixels

Finetuning

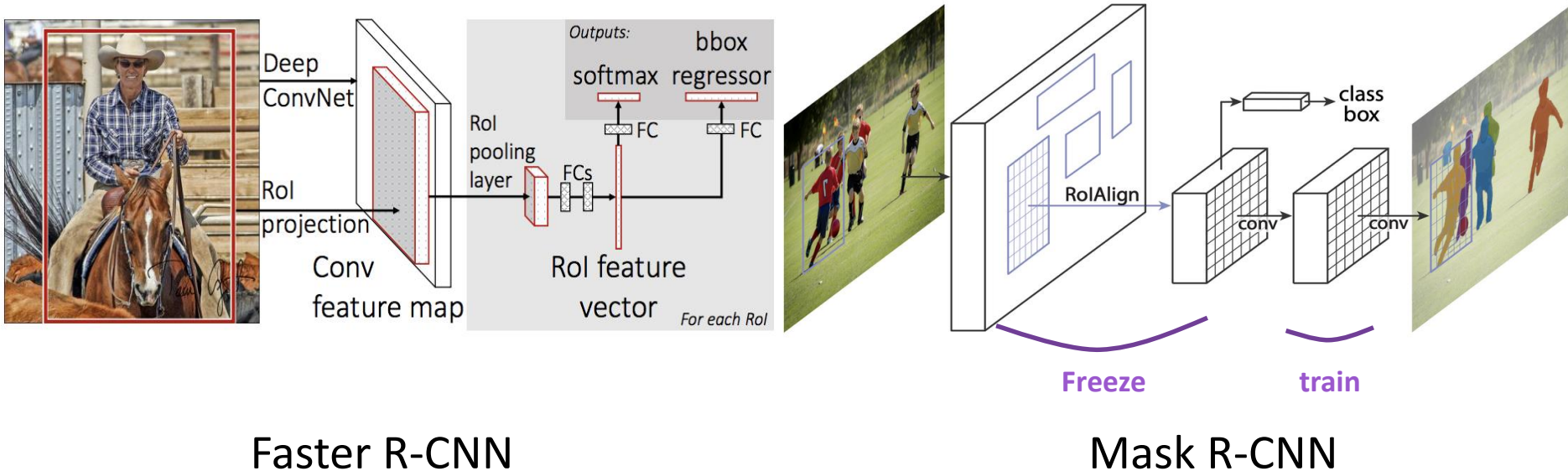
Fine-tuning Pretrained Network



source: <https://forums.fast.ai/t/training-layers-independently-and-backpropation/11862>

- In practice, very few people train an entire CNN with random initialization.
- Instead, use pre-trained model trained on a very large dataset.
- Then replace and retrain the classifier on top of the ConvNet on the new dataset.

Mask R-CNN



Faster R-CNN

Mask R-CNN

- Faster R-CNN is a model that predicts both bounding box and class scores in image.
- Mask R-CNN adds an extra branch into Faster R-CNN, which also predicts segmentation masks for each instance.
- We will use pre-trained Mask R-CNN (by COCO dataset) and finetune extra branch for segmentation.

How to install assignment files

- 포함된 파일: 3개
 1. Assignment2-1_CNN.ipynb
 2. Assignment2-2_CNN.ipynb
 3. CollectSubmission.sh
- 다운 후 설치 방법
 1. `$tar zxvf Assignment2.tar.gz` (decompress tar.gz file)
 2. `$cd Assignment2`
 3. `$chmod 755 CollectSubmission.sh` (get permission of script file)
 4. `$conda activate {가상환경명}`
 5. `$jupyter notebook`
- IPython notebook상에서 과제 수행

Score criteria

- Assignment_2-1 : 60 points + α
 - Problem 1 : Simple CNN model training on CIFAR-10 dataset (15 points)
 - Problem 2 : Inception module 구현
 - Problem 3 : Inception module을 활용한 CNN model training (45 points + α)
- Assignment_2-2 : 40 points
 - Problem 1 : Finetuning model 코드 구현 및 output visualization (40 points)
 - ✓ Evaluation score 상관없이 output visualization에 성공하면 40 points

Output Examples

- Assignment_2-1
- Problem 1 : Simple CNN model training on CIFAR-10 dataset

```
print_accuracy(net, testloader)
```

```
Accuracy of the network on the 10000 test images: 55 %
```

- Problem 3 : Inception module을 활용한 CNN model training (CIFAR-10)

```
[1, 2000] loss: 1.942
```

```
[1, 4000] loss: 1.616
```

```
[1, 6000] loss: 1.406
```

```
[1, 8000] loss: 1.278
```

```
[1, 10000] loss: 1.169
```

```
[1, 12000] loss: 1.088
```

```
[2, 2000] loss: 0.977
```

```
[2, 4000] loss: 0.936
```

```
[2, 6000] loss: 0.893
```

```
[2, 8000] loss: 0.830
```

```
[2, 10000] loss: 0.799
```

```
[2, 12000] loss: 0.762
```

```
Finished Training
```

```
Saved Trained Model
```

```
Accuracy of the network on the 10000 test images: 73 %
```

Output Examples

- Assignment_2-2
- Problem 1 : Finetuning model 코드 구현 및 output Visualization

```
IoU metric: bbox
Average Precision (AP) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.825
Average Precision (AP) @[ IoU=0.50 | area= all | maxDets=100 ] = 0.990
Average Precision (AP) @[ IoU=0.75 | area= all | maxDets=100 ] = 0.957
Average Precision (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = -1.000
Average Precision (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.569
Average Precision (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.835
Average Recall (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 1 ] = 0.383
Average Recall (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 10 ] = 0.871
Average Recall (AR) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.871
Average Recall (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = -1.000
Average Recall (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.800
Average Recall (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.877
IoU metric: segm
Average Precision (AP) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.763
Average Precision (AP) @[ IoU=0.50 | area= all | maxDets=100 ] = 0.990
Average Precision (AP) @[ IoU=0.75 | area= all | maxDets=100 ] = 0.917
Average Precision (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = -1.000
Average Precision (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.465
Average Precision (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.772
Average Recall (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 1 ] = 0.351
Average Recall (AR) @[ IoU=0.50:0.95 | area= all | maxDets= 10 ] = 0.809
Average Recall (AR) @[ IoU=0.50:0.95 | area= all | maxDets=100 ] = 0.809
Average Recall (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = -1.000
Average Recall (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.750
Average Recall (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.814
```

Evaluation result

(ignore -1.000 when area= small)



input image



output image

Important notes

- Due: 10/28(수) 23:59
- PLEASE read the notes on the notebooks carefully
- Google first before mailing TAs
- Submitting your work
 - DO NOT clear the final outputs
 - After you are done all two parts:
 1. \$./CollectSubmission.sh. 2000-00000 (학번)
 2. Upload the 2000-00000.tar.gz on eTL
- TA email : deeplearning.snu@gmail.com

FAQ_1

- Q : Batch size를 수정해도 되나요?
- A : 네. 모든 hyperparameter는 수정 가능합니다.
- Q : n3xn3_blue나 n5xn5_blue는 어떤 인자인가요?
- A : n3xn3_blue나 n5xn5_blue는 conv_layer의 output channel 수 입니다. 본인 원하시는 대로 output channel 개수를 조정하셔서 구현하시면 됩니다.
- Q : 주어진 inception module내에서 concat을 해주는데, 이때 tensor 크기를 고려해야 하나요?
- A : 주어진 모듈 내 forward의 리턴값을 보시면, torch.cat으로 y1,y2,y3,y4를 dimension 1에 대해 concat 해줍니다. PyTorch에서는 tensor를 batch x channel x height x width 순으로 정의하기 때문에 코드에서는 y1~4를 channel에 대해 concat 해주는 것입니다. 따라서 channel개수를 제외한 batch, height, width의 크기만 맞춰주시면 됩니다.

FAQ_2

- Q :.pth 파일이 무엇인가요?
- A : 학습 후 저장되는 모델 파일입니다. 학습을 완료하시면 자동생성됩니다.
- Q : max iteration 수나 data loader의 batch size, num_worker 수 등도 변경가능한지요?
- A : 가능합니다. 다만 batch size와 num_worker는 실험의 시간적인 면에서만 영향이 있고, 성능에는 영향이 거의 없을 것입니다.
- + epoch도 마찬가지로 기존2에서 더 늘려도 됩니다.
- Q : 코드 구현을 설명하는 부분도 점수에 포함되나요?
- A : ipynb 파일 마지막에 better_net에 관해 설명하는 부분은 copy 확인용이고 점수에 포함되지는 않습니다.
- 다만 Assignment 2-2의 3문제에 대한 답은 점수에 포함됩니다.
- Q : code 처음에 !는 무엇인가요?
- A : ! 뒤에 code는 shell script입니다. 즉, terminal에서 해당 code 돌리기 위해 사용되어집니다.

