Learning Deep Learning with PyTorch

(5) Techniques to improve CNNs performance

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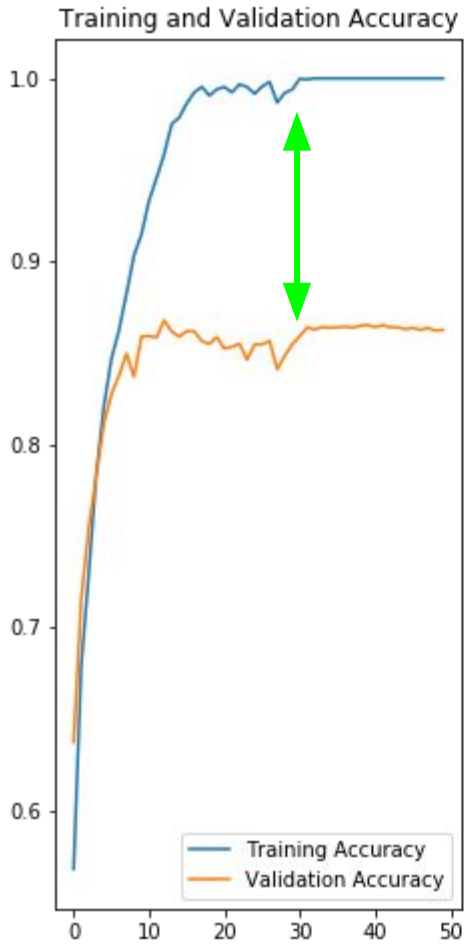
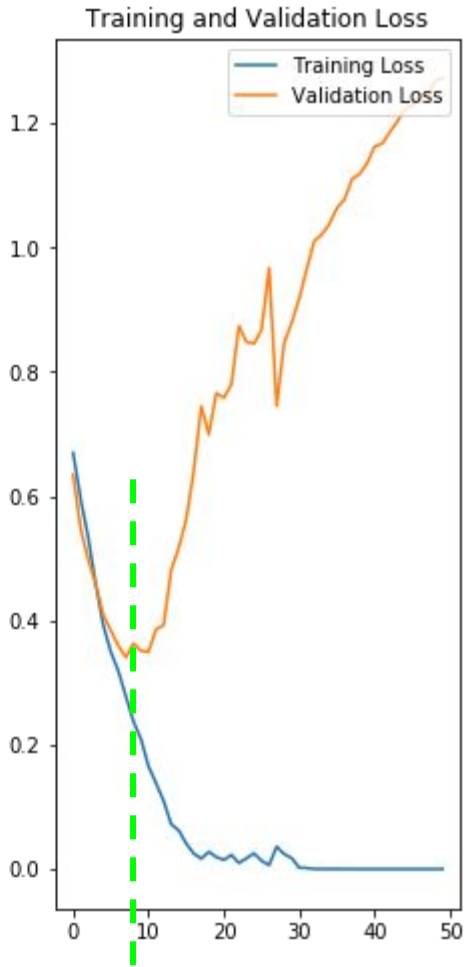
Quick Recap

- Dogs-vs-Cats challenges
  - 25,000 training images
  - 15,000 testing images
- Construct our own CNNs
  - 4 Conv layer blocks
  - Flatten layer
  - Dense layer
- Overfitting
  - Memorizing training set too much
  - Missing the essence knowledge
- How to improve?
  - Need more training data
  - Need regularization



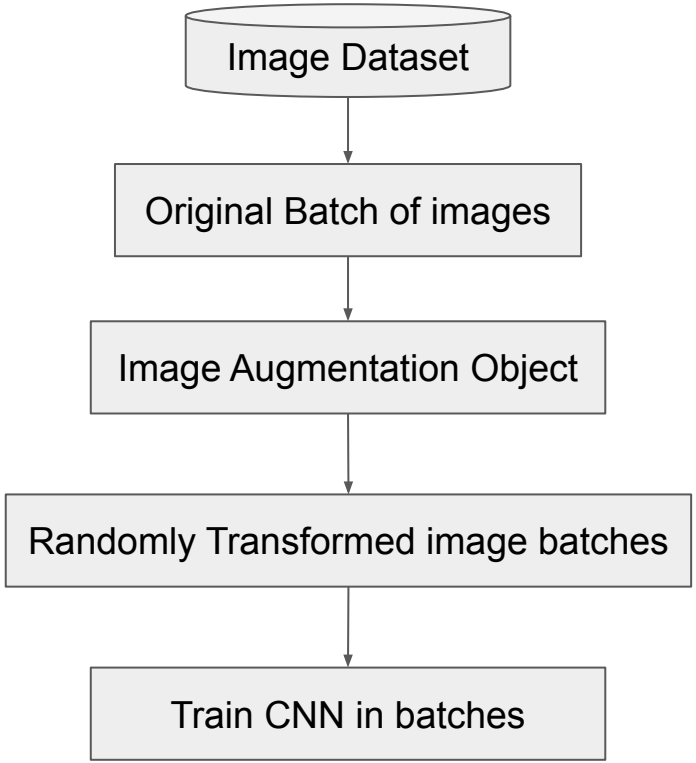


Dataset: the bigger the better, but why?

	VGGNet	DeepVideo	GNMT
Used For	Identifying Image Category	Identifying Video Category	Translation
Input	Image	Video	English Text
Output	1000 Categories	47 Categories	French Text
Parameters	140M	~100M	380M
Data Size	1.2M Images with assigned Category	1.1M Videos with assigned Category	6M Sentence Pairs, 340M Words

How to get more data with “no more”?

- Use data augmentation
  - Various transformations to the available dataset
  - Prevent the irrelevant data
- Types of data augmentation
  - Offline augmentation
    - Performing all the transformations beforehand
    - Good for smaller dataset
  - In-place augmentation
    - Performing transformations in mini-batches
    - Preferred for larger dataset
- Data augmentation in PyTorch
  - torchvision.transforms

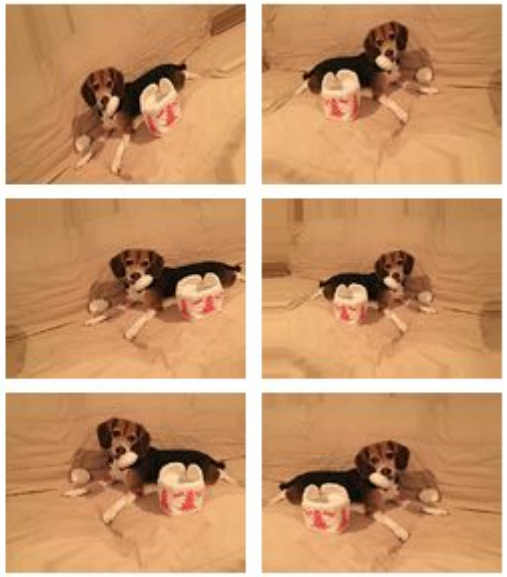


Augmentation Techniques

- Flip
- Affine Transformation
  - Rotation
  - Zoom & Crop
  - Translation
- Gaussian Noise
- ZCA whitening
- Histogram Equalization
- Feature-wise standardization
- Neural Style Transfer

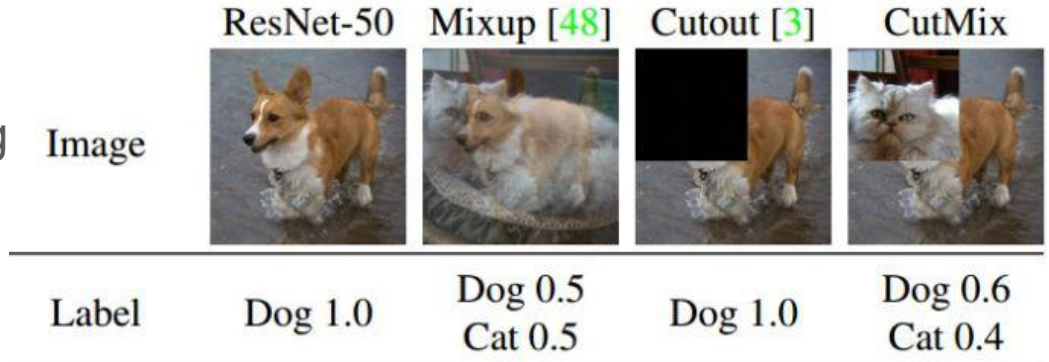
Input Image

Augmented Images



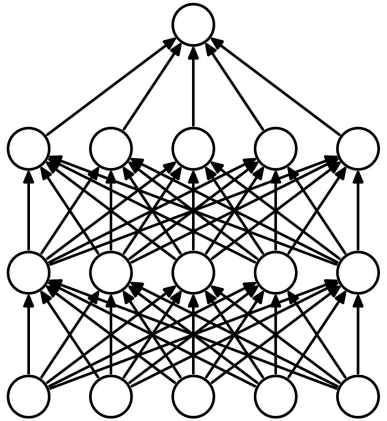
More Data Augmentation Techniques in CV tasks

- 3-D augmentation
- Random erasing
  - torchvision.transforms.RandomErasing(p=0.5, scale=(0.02, 0.33), ...)
  - Cutout (masking out random sections): no label change
  - Hide-and-seek, GridMask
  - Object Region Mining with Adversarial Erasing
- Mixup: soft overlapping
- Cutmix/Mosaic: hard masking
  - Cutmix: 2 images mixed
  - Mosaic: 4 images mixed

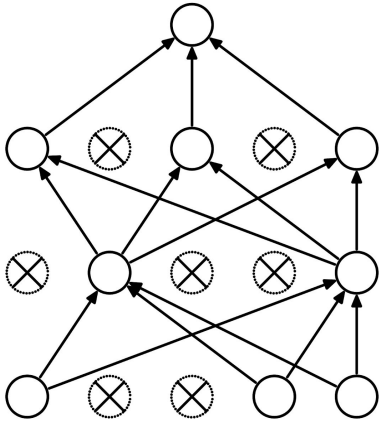


Drop-out technique

- Gradient vanishing during DNN training:
  - Imbalanced weights in network:
    - Larger weights => well trained
    - Smaller weights => not trained that much!
- Dropout: randomly turns off some neurons
  - Forcing networks to train weak neurons
  - Dropout rate: default 50%
    - Roughly double the iterations to converge
      Training time in epoch is less
  - Srivastava 2014 paper
  - Variations: spatial dropout, etc.
- PyTorch: torch.nn.Dropout2d()
  - Implemented by “Inverted dropout” technique
  - Apply to the corresponding layer(s)



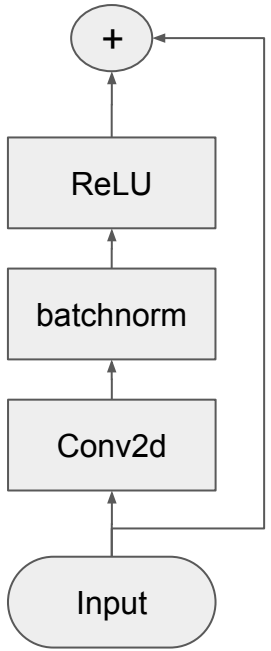
(a) Standard Neural Net



(b) After applying dropout.

Other training techniques in deep learning

- Regularizer
  - l1(Lasso), l2(Ridge), l1_l2(ElasticNet) in each layer
    - weight_decay flag for l2 in pytorch optimizers
- Early Stopping
  - Stop training when validation loss reach minimum
- Batch Normalization
  - Normalize the data (input features) across batches in each mini-batch
  - Add batch normalization before activation function
    - torch.nn.BatchNorm2D(num_features=n_chans1)
- Skip connections
  - Simple trick to add the input (conv1) to the output of a block of layers (conv3)
  - Residual networks (K. He, 2015)
    - Opened the door to hundreds-layer-depth networks (Highway Net, U-Net, Dense-Nets, …)

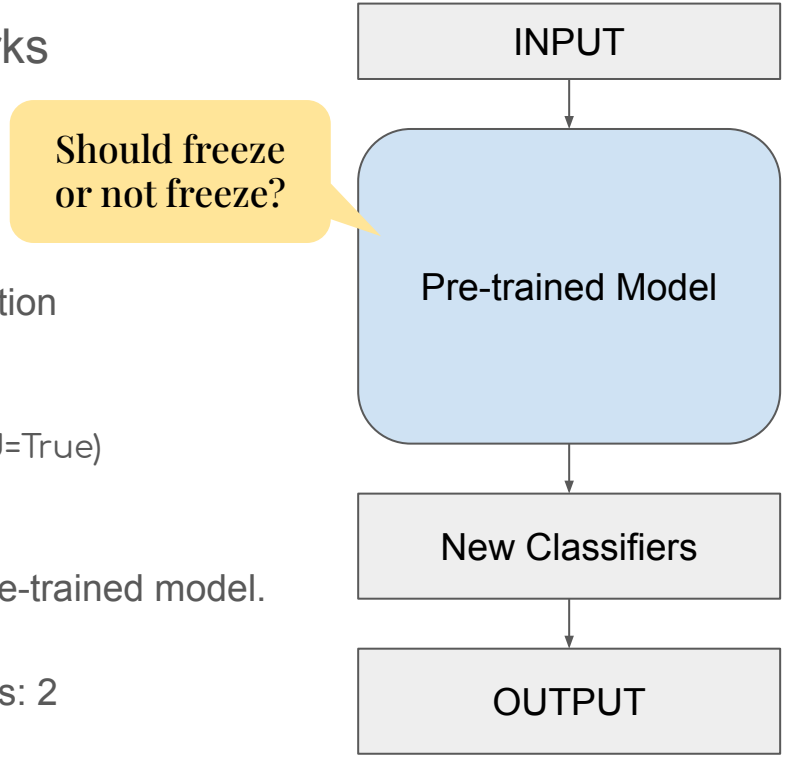


Colab Hands-on

bit.ly/LDL_03

Transfer Learning

- Reusing the developed neural networks
  - Greatly speed up our training
  - Make it mobile
- Image classification
  - Advanced models from ImageNet competition
    - AlexNet, ResNet, Inception v3, …
  - torchvision.models
    - resnet = models.resnet152(pretrained=True)
- Simple steps
  - Match the input size of images from the pre-trained model.
  - Define our new classifiers
    - ImageNet classes: 1280; Our classes: 2



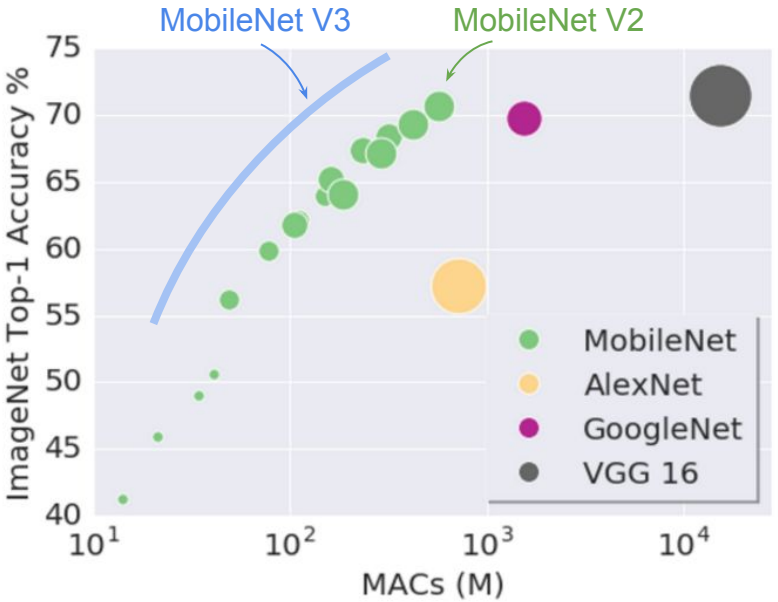
MobileNet v2 & v3

- Very efficient CNNs (v2 paper & v3 paper)
  - Especially good for mobile vision apps
- PyTorch Hub
  - Pretrained models from the latest research
  - Published through GitHub
    - Check hubconf.py
- Loading the model from Hub

```
model = torch.hub.load( 'pytorch/vision:v0.5.0',
                        'mobilenet_v2',
                        pretrained=True
                        )
```

- Modify the classifier layer

```
model.classifier[1] = torch.nn.Linear(1280, 2)
```

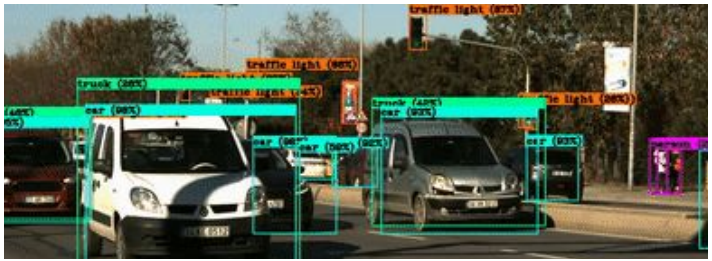


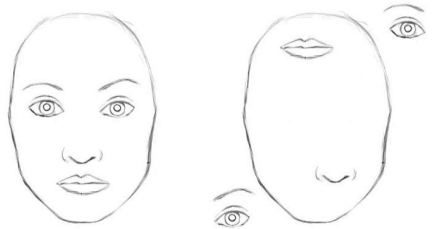
(MACs = Multiply-Accumulates)

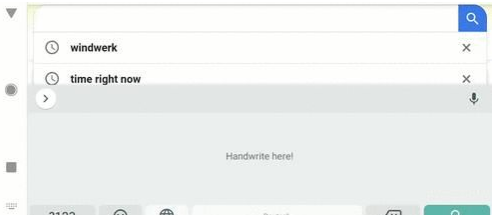
Figure from v2 paper and v3 paper

Other CV Topics

- Classifying from images to regions
  - R-CNN, Fast R-CNN, Faster R-CNN
  - Mask R-CNN, R-FCN, SSD, RetinaNet
  - YOLOv5, ...
- Improving classification:
  - Adversarial Attacks
  - Capsule Networks
    - spatial hierarchies to inverse graphics
- Recurrent Neural Networks
  - Dynamic input and output layers
  - Especially effective in sequence problems
- Transformer-based CNNs







FYI

- Github Repo:
  - https://github.com/huqy/idre-learning-deep-learning-pytorch
- Slack workspace:
  - bit.ly/join-LDL
- Contact me
  - huqy@idre.ucla.edu
  - Direct message in Slack