# Learning Convolutional Neural Networks (2)

Qiyang Hu
UCLA Office of Advanced Research Computing
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# In this talk

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## Improving our model

- Data Augmentation
- Dropout & batch norm
- Demo

01

## Transfer learning

- Transferring knowledge
- MobileNet
- Demo

02

## Latest Developments

- ViT & Swin-T
- ConvViT & ConvNeXt

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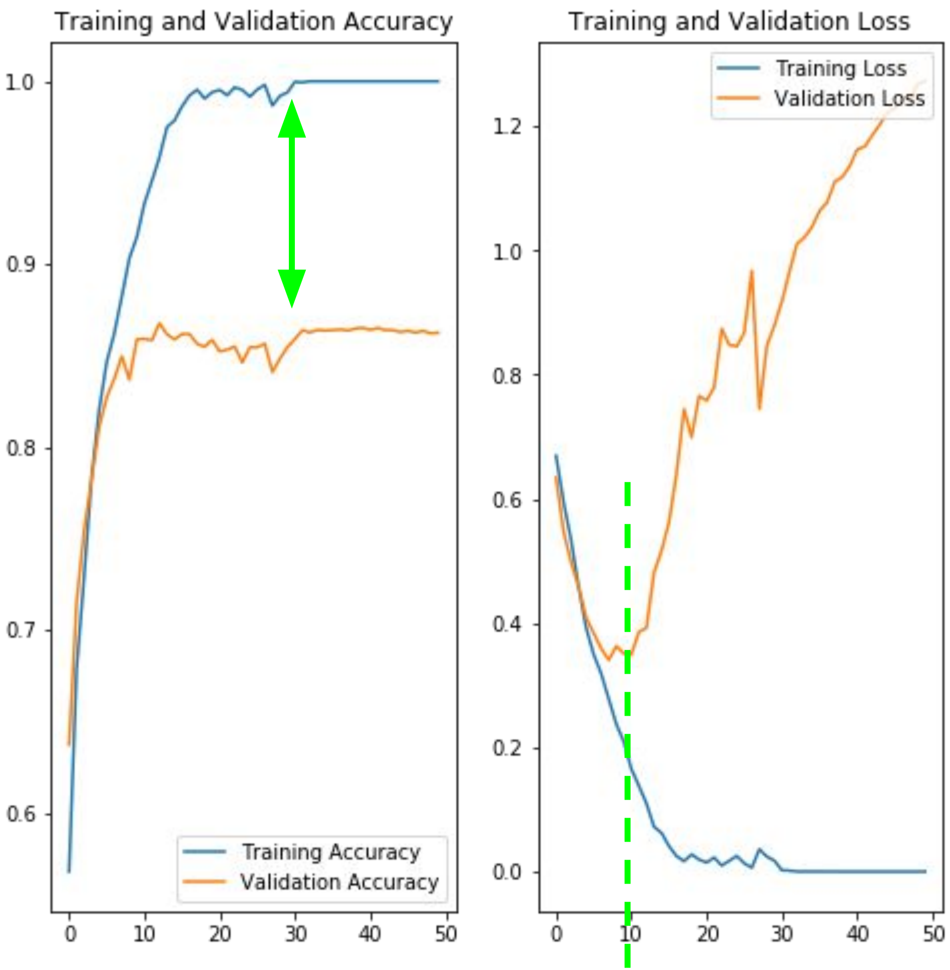
# Quick Recap

- 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

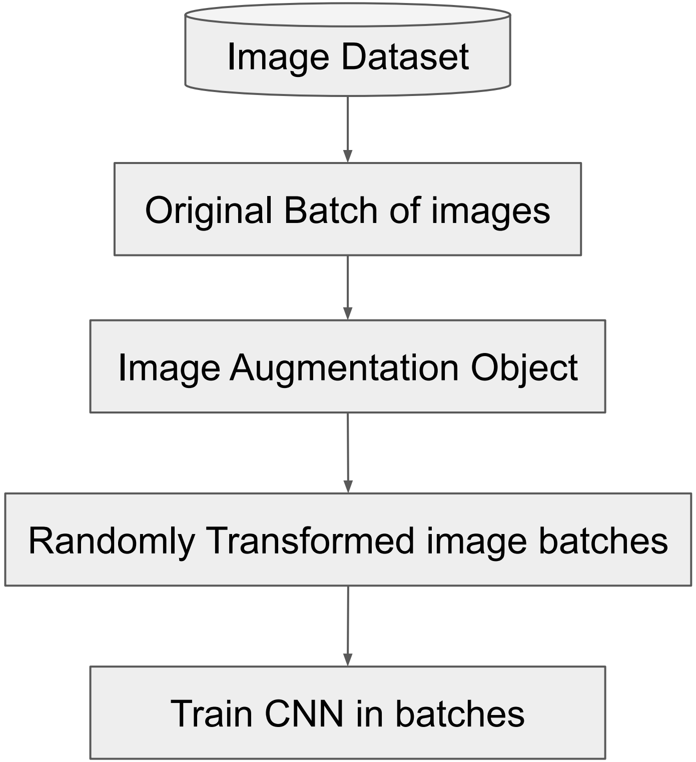


# Data and models: the bigger the better, *really*?

| | VGGNet | DeepVideo | GNMT | GPT-3 |
|---|---|---|---|---|
| Used For | Identifying Image Category | Identifying Video Category | Translation | Text Generation |
| Input | Image | Video | English Text | Text |
| Output | 1000 Categories | 47 Categories | French Text | Text |
| Parameters | 140M | ~100M | 380M | 175B |
| Data Size | 1.2M Images with assigned Category | 1.1M Videos with assigned Category | 6M Sentence Pairs, 340M Words | 2TB of Internet Text ~ 499 Billion Tokens |

# From big size to smart size

- Using data augmentation
  - To get more data with “no more”
  - 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

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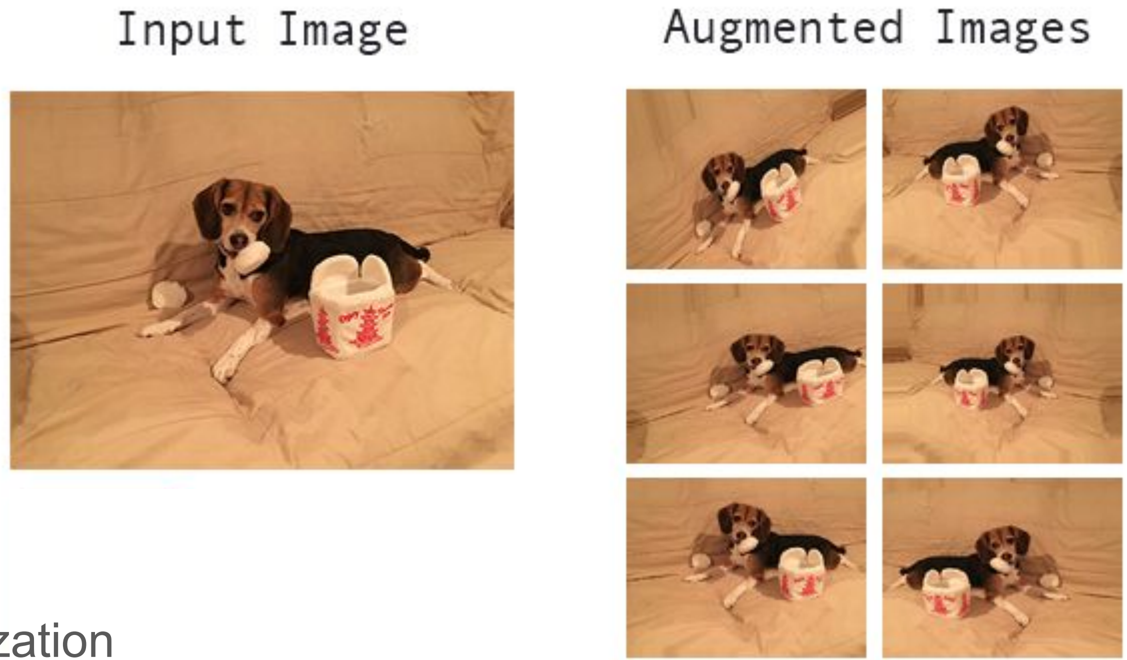
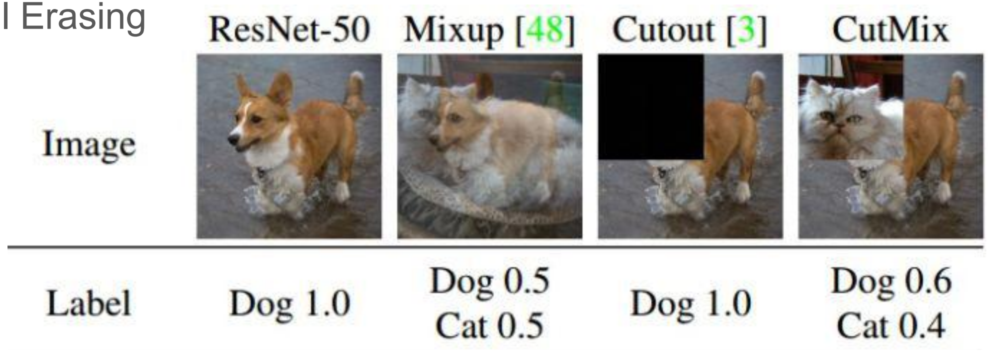
# Augmentation Techniques

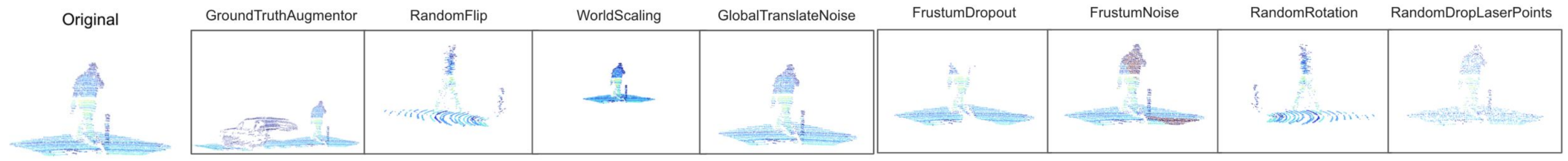
- Flip
- Affine Transformation
  - Rotation
  - Zoom & Crop
  - Translation
- Gaussian Noise
- ZCA whitening
- Histogram Equalization
- Feature-wise standardization
- Neural Style Transfer



# More Data Augmentation Techniques in CV tasks

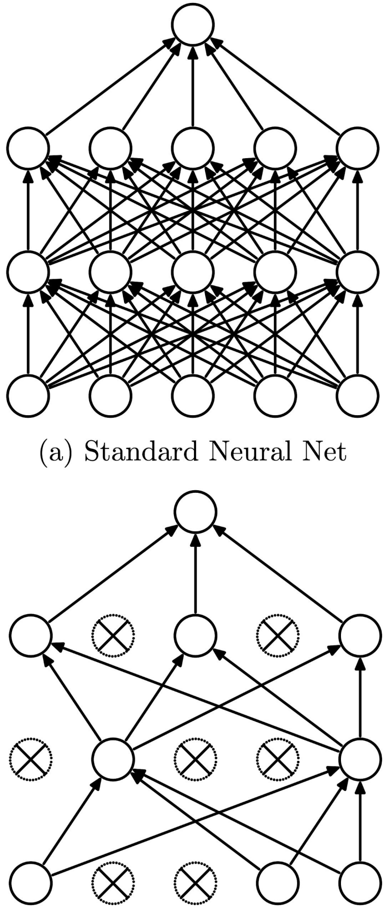
- Random erasing: torchvision.transforms.RandomErasing(p=0.5, scale=(0.02, 0.33), ...)
    - Cutout (masking out random sections): no label change
    - Hide-and-seek, GridMask
    - Object Region Mining with Adversarial Erasing
- Mixup: soft overlapping
- Cutmix/Mosaic: hard masking
    - Cutmix: 2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



# 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)

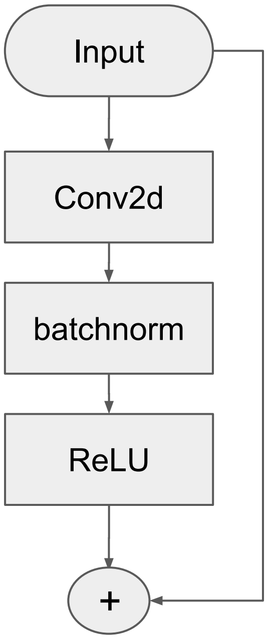


(a) Standard Neural Net

(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](K. He, 2015))
    - Opened the door to hundreds-layer-depth networks (Highway Net, U-Net, Dense-Nets, …)



# Colab Hands-on

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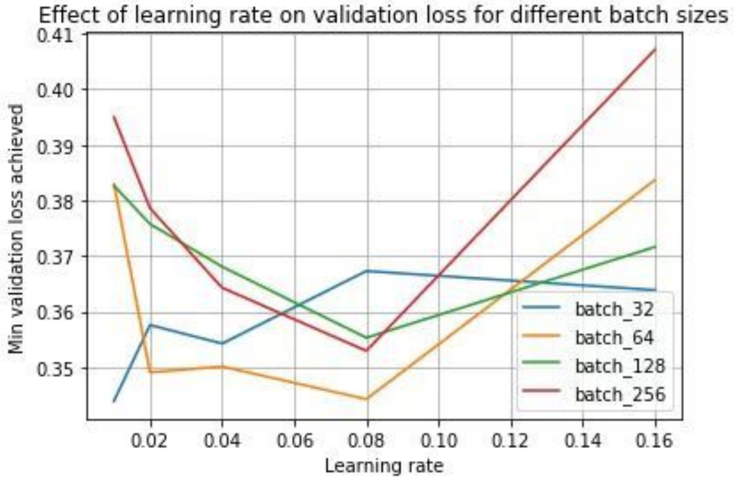
# Tips of CNNs

- Design
  - Kernels
    - Shape: square for visual tasks, rectangles for NLPs
    - Size: odd x odd, (3x3, 5x5, 7x7)
  - Number of Conv Layers:
    - Start with a few
    - < 100
- Hyperparameters:
  - Batch size: neither too big, nor too small
    - start from 16, then 8 or 32
  - Learning rate: start from 0.01
    - minibatch size * k ⇒ learning rate * k
  - Use batch normalization
  - Use random search

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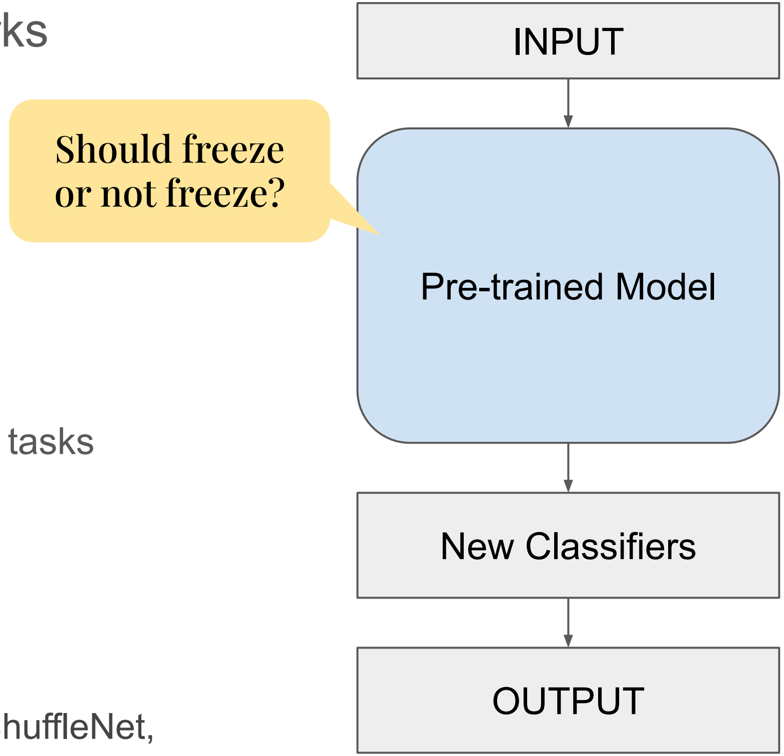
# Transfer Learning

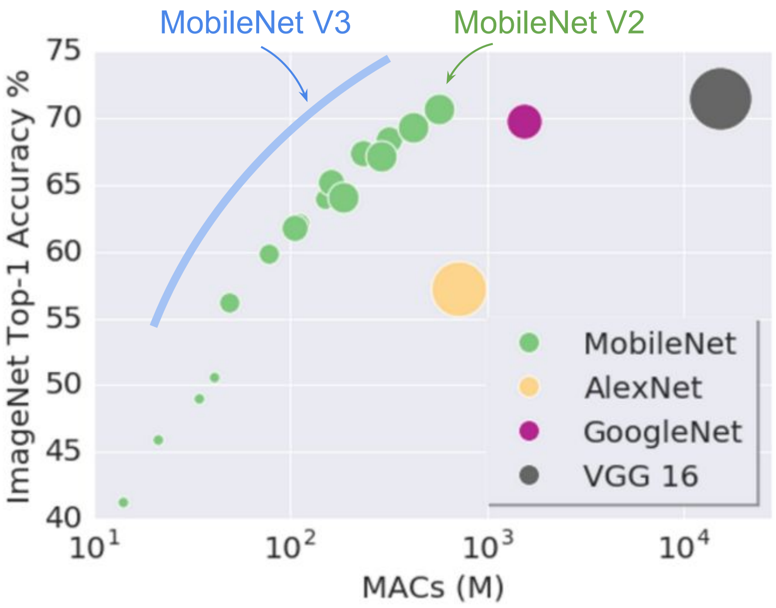
- Reusing the developed neural networks
  - Greatly speed up our training
  - Make it mobile
- Reused model ⇒ feature extractor
  - Pre-trained on a popular generic dataset
  - Transfer the knowledge
    - Match the input
    - Add new layers for specific data and tasks
- Two trends of pre-trained models
  - Gigantic backbones: ResNet, BERT
  - Light-fast-efficient backbones:
    - SqueezeNet, MobileNet v1, v2
    - MobileNet v3, TinyYOLO, MnasNet, ShuffleNet, CondenseNet, ESPNet, DiCENet, MixNet, EfficientNet



# MobileNet

- Very efficient CNNs (v2 paper & v3 paper)
  - Depthwise separable convolutions
  - Inverted residual with linear bottleneck
  - Squeeze-and-excitation (SE) modules
- Loading the model:
  - MobileNet v2:
    - torchvision.models
    - PyTorch Hub
  - MobileNet v3:
    - large, small and quantized
    - torchvision.models.mobilenet_v3_…
- Modify the classifier layer

model.classifier[3] = torch.nn.Linear(1280, 2)




(MACs = Multiply-Accumulates)

Figure from v2 paper and v3 paper

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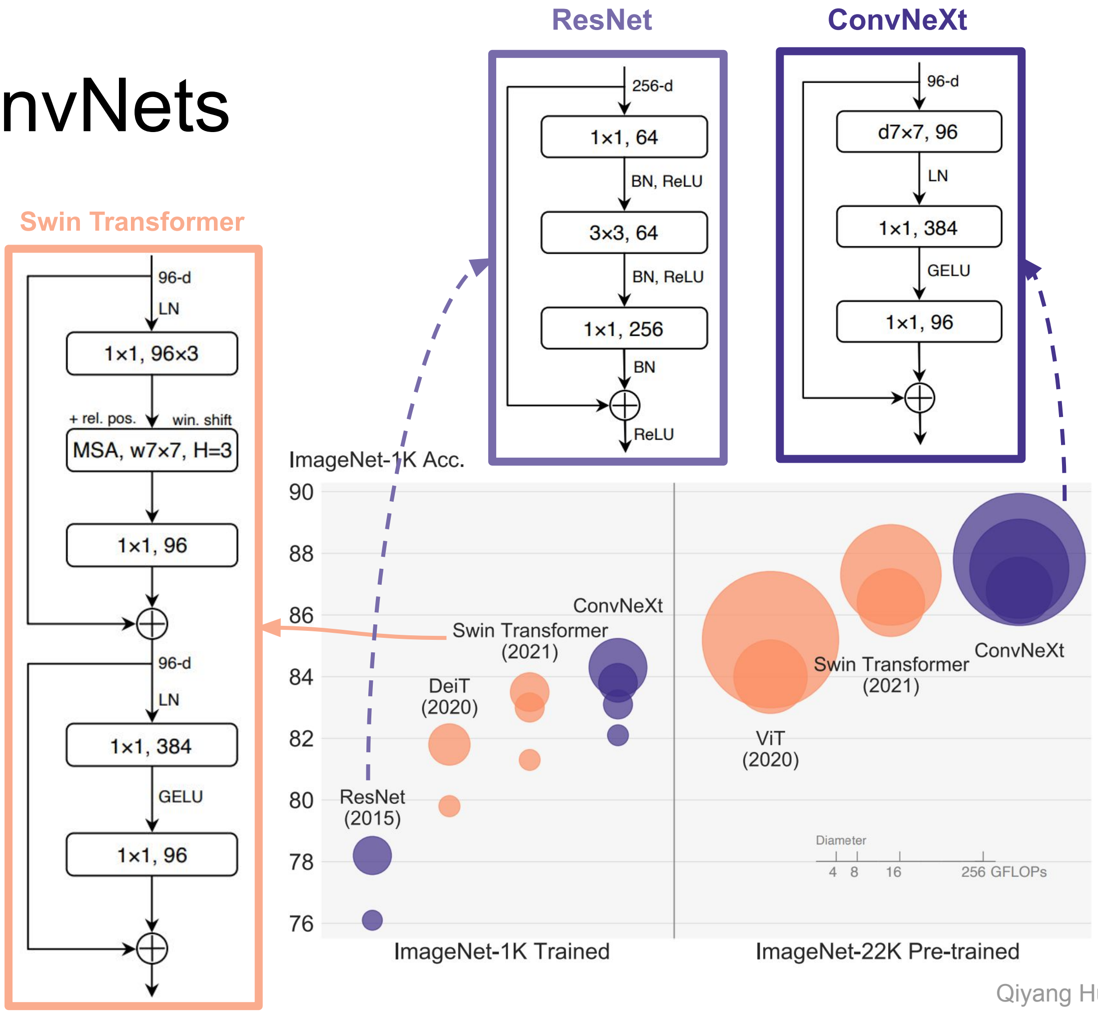
# A Twist of Modern ConvNets

- Renaissance since 2012
  - AlexNet, VGGNet, ResNet, MobileNet, EfficientNet, …
  - Rapid development due to
    - "Sliding window"
    - Translation equivariance
- Challenges from NLP (2020)
  - Vision Transformers (ViT), Swin Transformers (Swin-T)
  - Replacing ConvNet by:
    - Split img to a seq of patches
    - Permutation invariant via self-att
- Revival since 2021
  - ConViT (2021), [ConvNeXt (2022)]



# Survey

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