HW2 Bootcamp

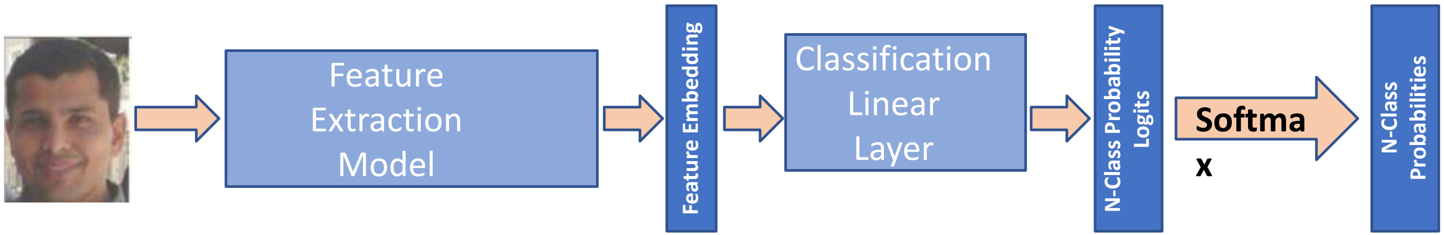
Logistics

- HW2P2 is **significantly harder** than HW1P2. Models will be harder to develop, train, and converge. Please start early!
- Models must be written yourself and trained from scratch.
- You may use CMU Virtual Andrew (8GB Nvidia L40, 32 GB RAM) for training.

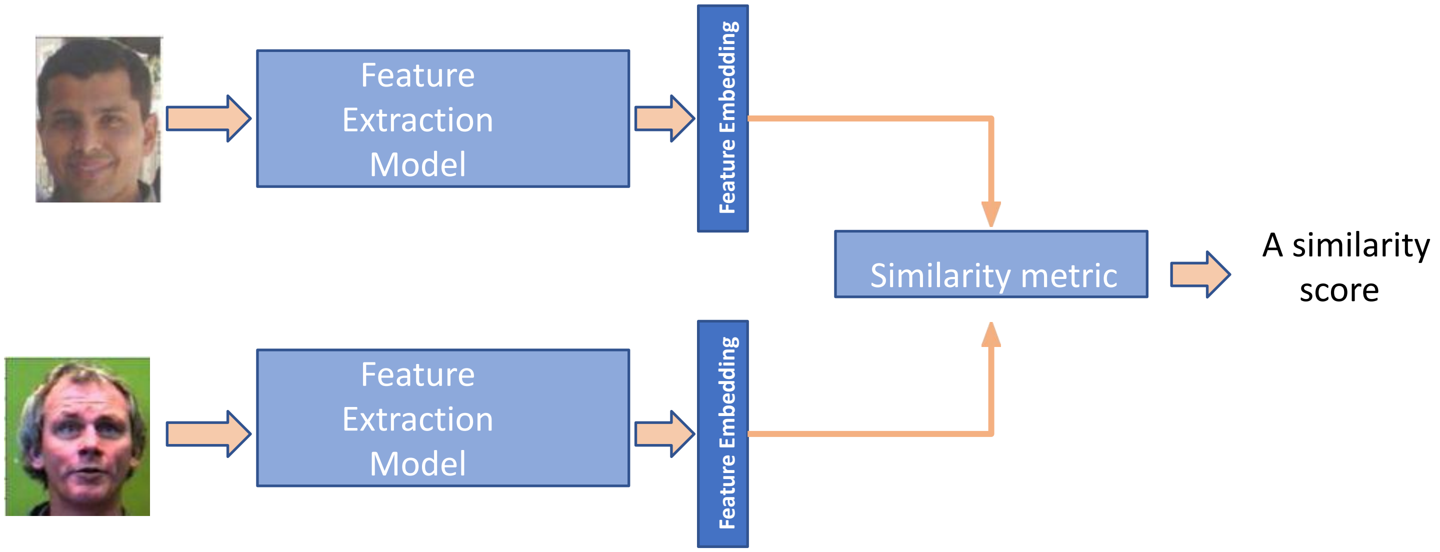
Problem Statement

- **Face Classification**
  - Given an image, figure out which person it is.
- **Face Verification**
  - Given a set of images, figure out if they are of the same person.

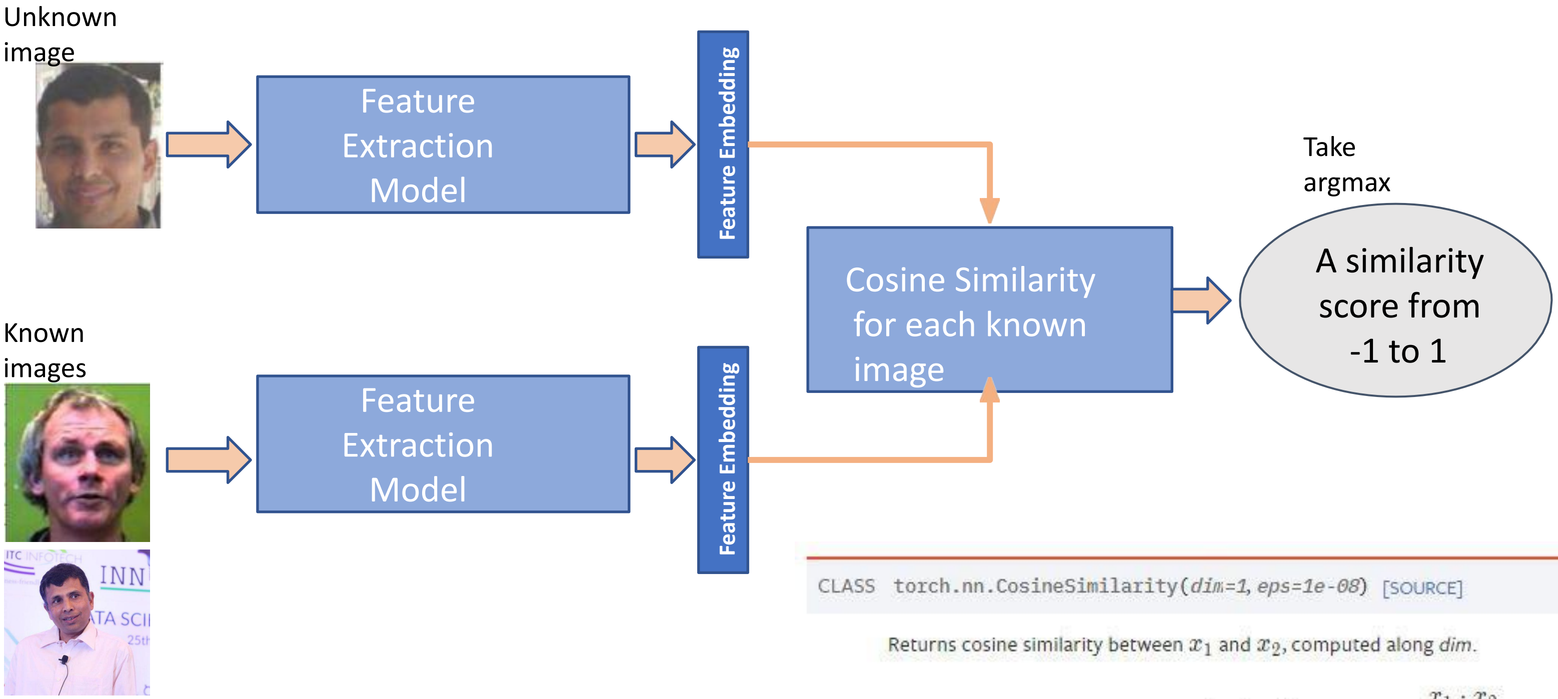
Face Classification



Face Verification



Face Verification



CLASS torch.nn.CosineSimilarity(*dim=1, eps=1e-08*) [SOURCE]

Returns cosine similarity between x_1 and x_2, computed along *dim*.

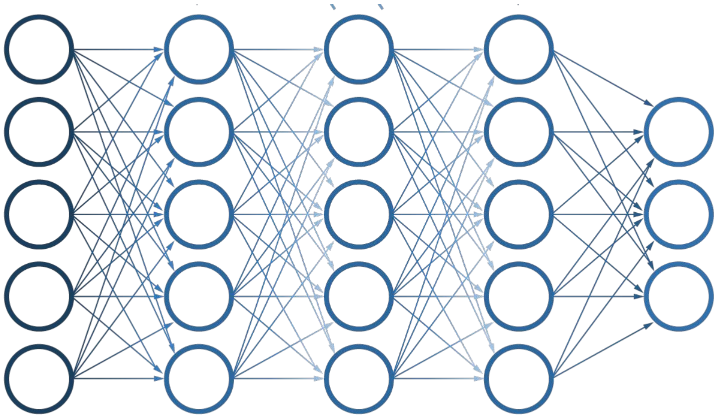
$$\text{similarity} = \frac{x_1 \cdot x_2}{\max(\Vert x_1 \Vert_2 \cdot \Vert x_2 \Vert_2, \epsilon)}.$$

Workflow

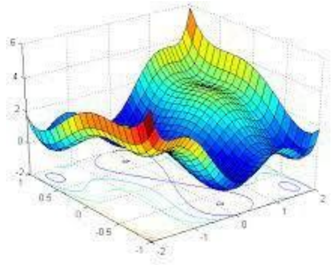
- First train a strong classification model for the classification task.
- Then, for the verification task, use the model trained on classification.
  - take the penultimate features as feature embeddings of each image.
- You should additionally train verification-specific losses such as ArcFace, Triplet Loss to improve performance.

Building Blocks

Input Image +
Transformations

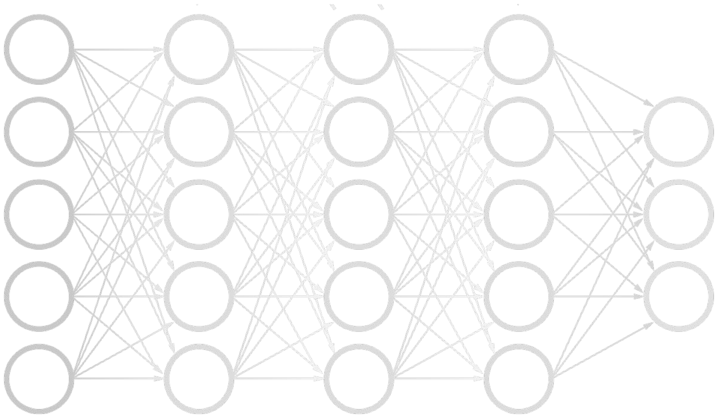


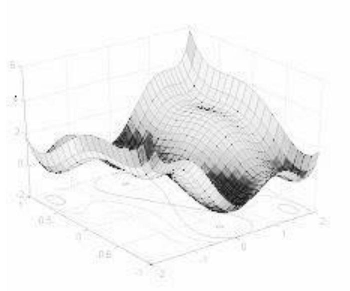
Choice of
Model



Training the
model

Building Blocks



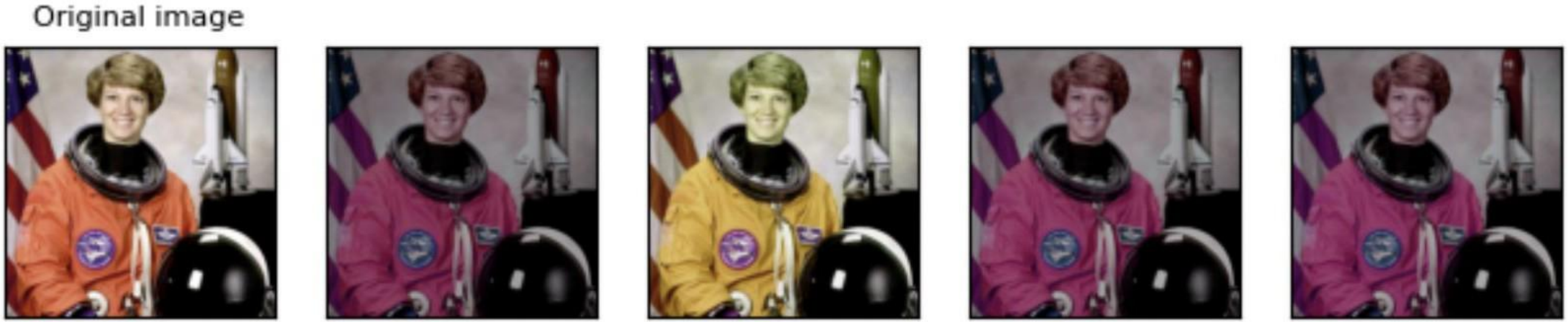


Input Image +
Transformations

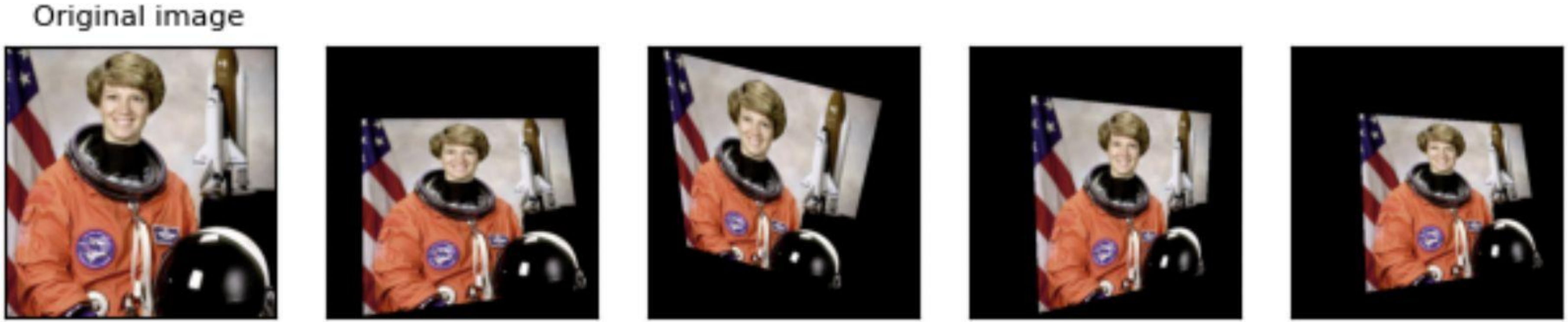
Choice of
Model

Training the
model

Color Jitter



Random Perspective



Random Vertical Flip

Transformation Guide

URL:
https://pytorch.org/vision/stable/auto_examples/plot_transforms.html#sphx-glr-auto-examples-plot-transforms-py

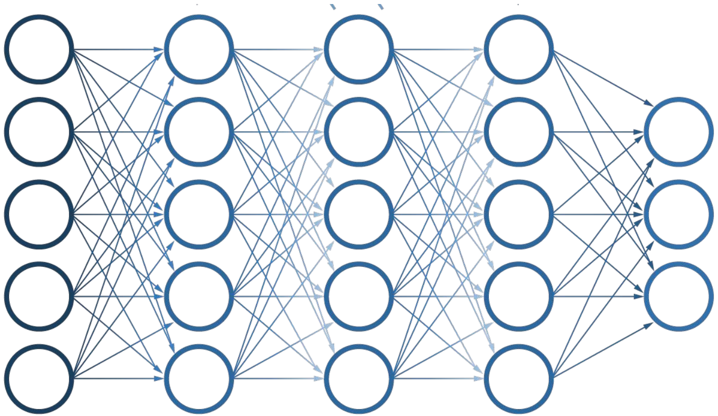
Common Issue:

`TypeError: Input tensor should be a torch tensor. Got <class 'PIL.Image.Image'>.`

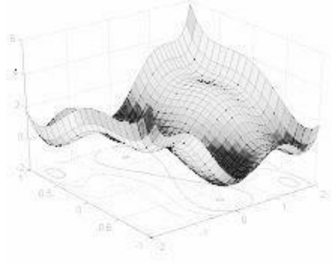
—> *Please check the sequencing of your transforms. Read the documentation and verify the kind of input required.*

Building Blocks

Input Image + Transformation
s



Choice of Model

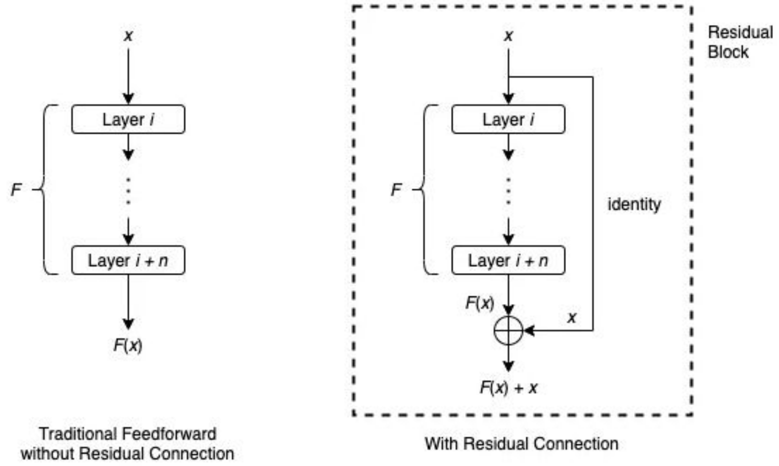


Training the model

Residual Connections

In traditional feedforward neural networks, data flows through each layer **sequentially**: The output of a layer is the input for the next layer.

Residual connection provides another path for data to reach latter parts of the neural network by **skipping** some layers.

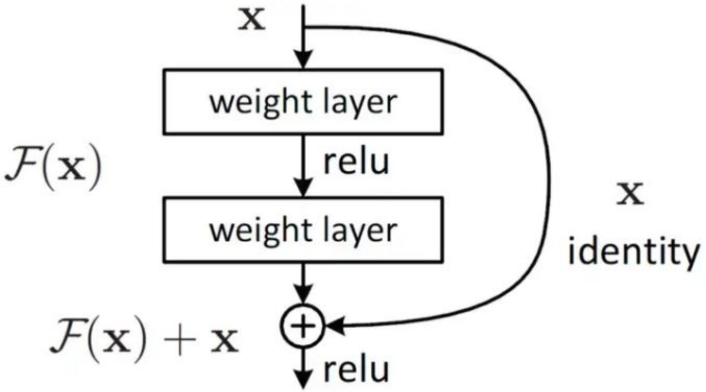


Residual Connections

- The residual connection first applies identity mapping to x
- Then it performs element-wise addition $F(x) + x$.
- The whole architecture that takes an input x and produces output $F(x) + x$ is usually called a residual block or a building block.
- Quite often, a residual block will also include an activation function such as ReLU applied to $F(x) + x$.

How do they help??

- For feedforward neural networks, training a deep network is usually very difficult, due to problems such as **exploding gradients and vanishing gradients**.
- On the other hand, the training process of a neural network with residual connections is empirically shown to converge much more easily, even if the network has several hundreds layers.
- It is easier to learn Zero weights than an Identity mapping, if the residual connections aren't present.



ResNet Block

- Remember that to understand a paper, we just really need to understand its **blocks**.
- ResNet proposes 2 blocks: BasicBlock & BottleneckBlock
- The key point is residual connection

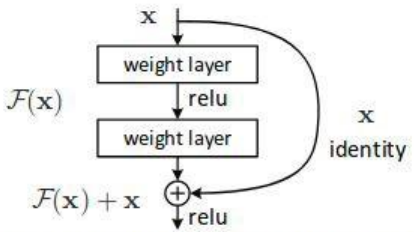
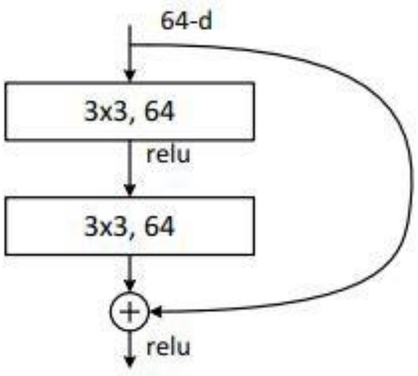


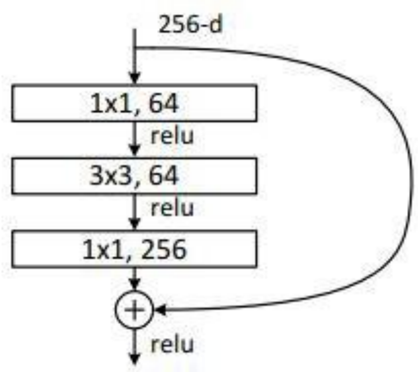
Figure 2. Residual learning: a building block.

ResNet: BasicBlock



- It’s just a regular 3x3 convolution (then BN, ReLU), another 3x3 convolution (then BN).
- Then, a skip connection adding input and output, then ReLU.

ResNet: BottleneckBlock



- A bit more involved.
- A 256-channel input goes through a point-wise convolution, reducing channels to 64.
- Then, a 3x3 regular convolution maintains channels at 64.
- Then, a point-wise convolution expands channels back to 256.
- Finally, the residual connection.

Basic and Bottleneck Block

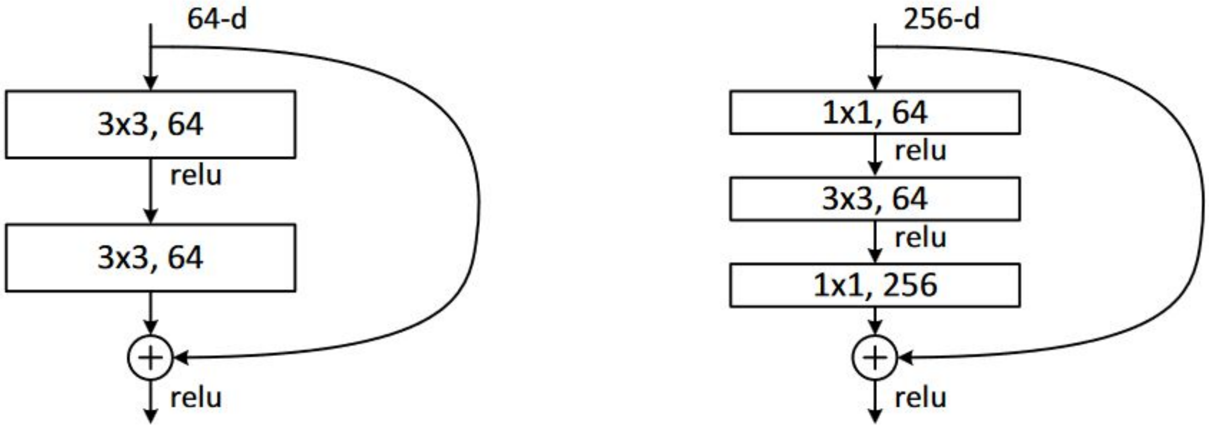


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

Residual Connection - Basic Block

```python
class BasicBlock(torch.nn.Module):

  def __init__(self, n_h):

    self.linear0 = torch.nn.Linear(n_h, n_h)
    self.linear1 = torch.nn.Linear(n_h, n_h)

    self.bn0 = torch.nn.BatchNorm1d(n_h)
    self.bn1 = torch.nn.BatchNorm1d(n_h)

    self.relu = torch.nn.ReLU(inplace=True)
```

```python
def forward(self, A0):

  R0  = A0

  Z0  = self.linear0(A0)
  BZ0 = self.bn0(Z0)
  A1  = self.relu(BZ0)

  Z1  = self.linear1(A1)
  BZ1 = self.bn1(Z1)
  A2  = self.relu(BZ1 + R0)

  return A2
```

Residual Connection - Bottleneck Block

```python
class Bottleneck(torch.nn.Module):

  def __init__(self, n_h):

    self.residual = torch.nn.Linear(n_h, n_h*4)

    self.linear0 = torch.nn.Linear(n_h, n_h  )
    self.linear1 = torch.nn.Linear(n_h, n_h  )
    self.linear2 = torch.nn.Linear(n_h, n_h*4)

    self.bn0 = torch.nn.BatchNorm1d(n_h  )
    self.bn1 = torch.nn.BatchNorm1d(n_h  )
    self.bn2 = torch.nn.BatchNorm1d(n_h*4)

    self.relu = torch.nn.ReLU(inplace=True)
```

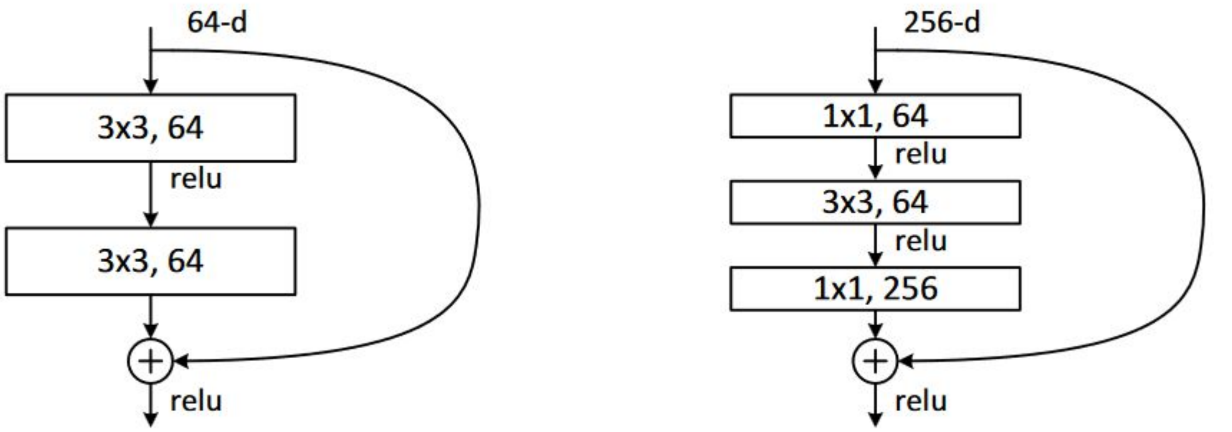
```python
def forward(self, A0):
  R0  = self.residual(A0)

  Z0  = self.linear0(A0)
  BZ0 = self.bn0(Z0)
  A1  = self.relu(BZ0)

  Z1  = self.linear1(A1)
  BZ1 = self.bn1(Z1)
  A2  = self.relu(BZ1)

  Z2  = self.linear2(A2)
  BZ2 = self.bn2(Z2)
  A3  = self.relu(BZ2 + R0)
  return A3
```

Basic and Bottleneck Block



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Architectures

- At this point, you should have basic familiarity with convolutions as taught in lecture.
- Now, how do we take convolutions and assemble them into a strong architecture?
  - Layers? Channel size? Stride? Kernel Size? Etc.
- We'll cover three different types of blocks:
  - **Resnet blocks**
  - Convnext blocks
  - Mobile blocks

General Architecture Flow

- CNN architectures are divided into stages, which are divided into blocks.
  - Each “stage” consists of (almost) equivalent “blocks”
  - Each “block” consists of a few CNN layers, BN, and ReLUs.
- To understand an architecture, we mostly need to understand its **blocks**.
- All that changes for blocks in different stages is the base # of channels

General Architecture Flow

- However, you do need to piece these blocks together into a final model.
- The general flow is like this:
  - Stem
  - Stage 1
  - Stage 2
  - …
  - Stage n
  - Classification Layer

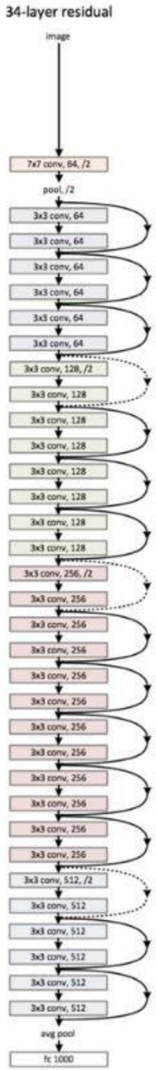
General Architecture Flow

- The stem usually downsamples the input by 4x.
- Some stages do downsample. If they do, generally, the first convolution in the stage downsample by 2x.
- When you downsample by 2x, you usually increase channel dimension by 2x.
  - So, later stages have smaller spatial resolution, higher # of channels

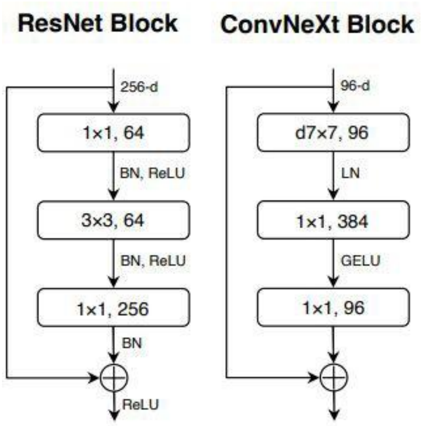
ResNet: Overall

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 2. Sizes of outputs and convolutional kernels for ResNet 34



ConvNeXt: Block

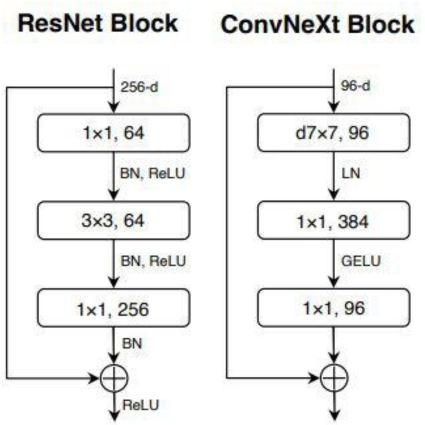


- A 7x7 depth-wise convolution.
- A point-wise convolution increasing # of channels
- A point-wise convolution decreasing # of channels
- Residual Connection

ConvNeXt block

- This is a very new paper, a state-of-the-art architecture.
- However, **its intuitions are very similar to MobileNetV2.**
- Again, remember that to understand a paper, we just really need to understand its **blocks**.
- Just a single block type for ConvNeXt
- **Read the paper** for details on stages/channel sizes, etc.
    - We recommend **ConvNeXt-T size** which has less than 35M parameters.

ResNet vs ConvNeXt: Differences



- Note that ConvNeXt has fewer BN/ReLU
  - GELU is just more advanced ReLU
  - Dubey, Shiv Ram, Satish Kumar Singh, and Bidyut Baran Chaudhuri. "Activation functions in deep learning: A comprehensive survey and benchmark." Neurocomputing (2022).

ResNet vs ConvNeXt

	output size	• ResNet-50	• ConvNeXt-T
stem	56×56	7×7, 64, stride 2 3×3 max pool, stride 2	4×4, 96, stride 4
res2	56×56	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} d7\times7, 96 \\ 1\times1, 384 \\ 1\times1, 96 \end{bmatrix} \times 3$
res3	28×28	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} d7\times7, 192 \\ 1\times1, 768 \\ 1\times1, 192 \end{bmatrix} \times 3$
res4	14×14	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} d7\times7, 384 \\ 1\times1, 1536 \\ 1\times1, 384 \end{bmatrix} \times 9$
res5	7×7	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} d7\times7, 768 \\ 1\times1, 3072 \\ 1\times1, 768 \end{bmatrix} \times 3$
FLOPs		4.1×10^9	4.5×10^9
# params.		25.6×10^6	28.6×10^6

Mobile Block

- The goal of MobileNet blocks is to be parameter efficient.
- They do so by making extensive use of **depth-wise convolutions** and **point-wise convolutions**

A Normal Convol

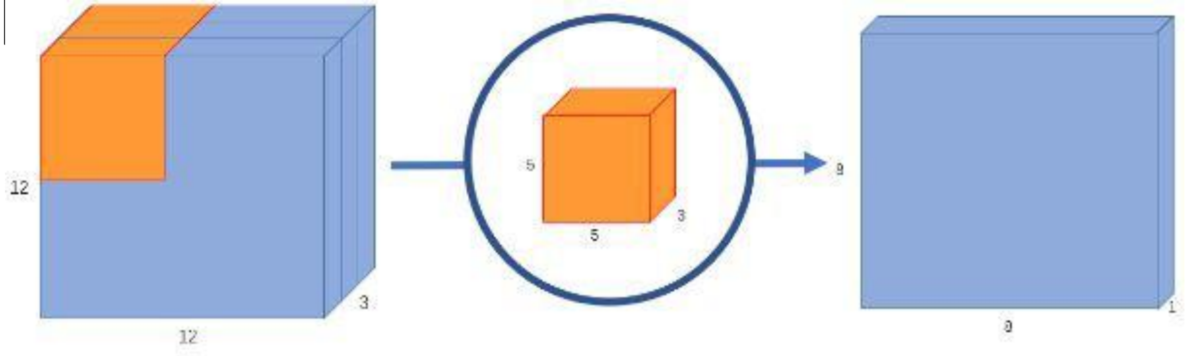


Image 4: A normal convolution with 8×8×1 output

- Considering just a single output channel

A Normal Convolution (Another Diagram)

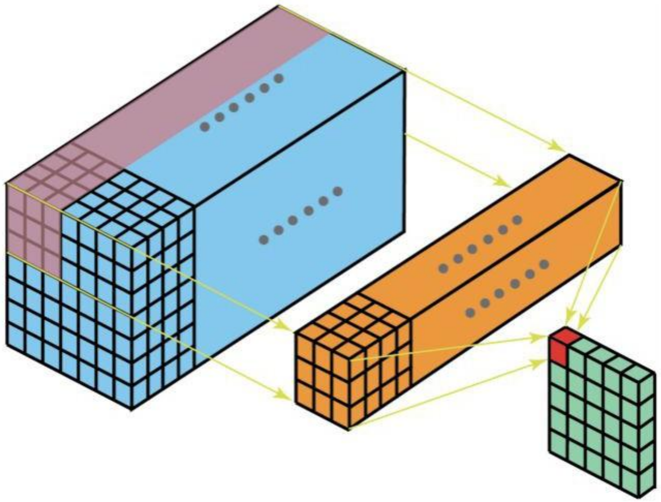


Fig. 2: Functional interpretation of 2D convolution (source)

- Considering a single output channel

A Normal Convolut

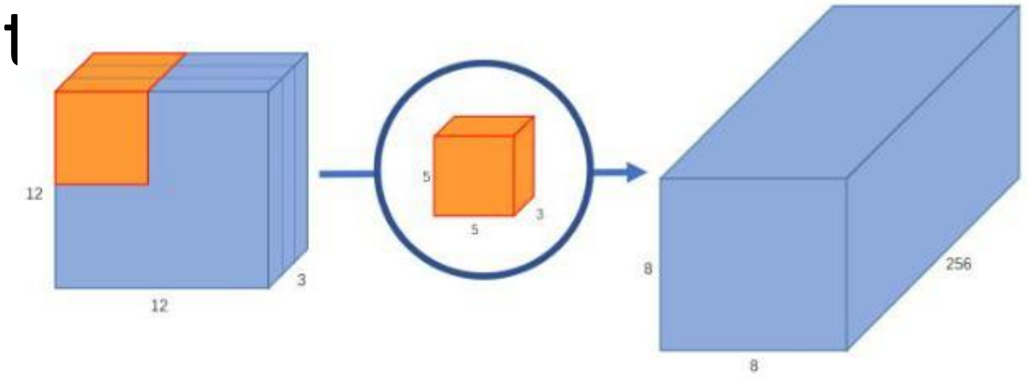
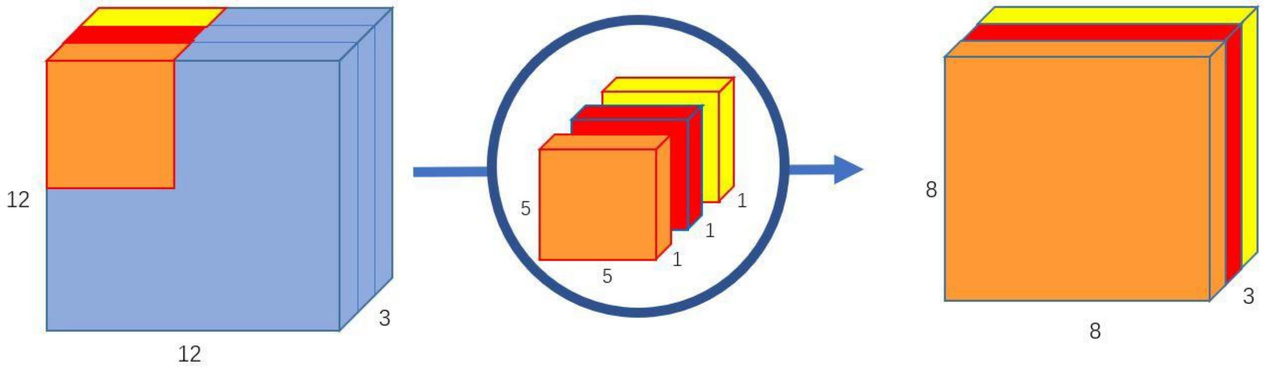


Image 5: A normal convolution with 8×8×256 output

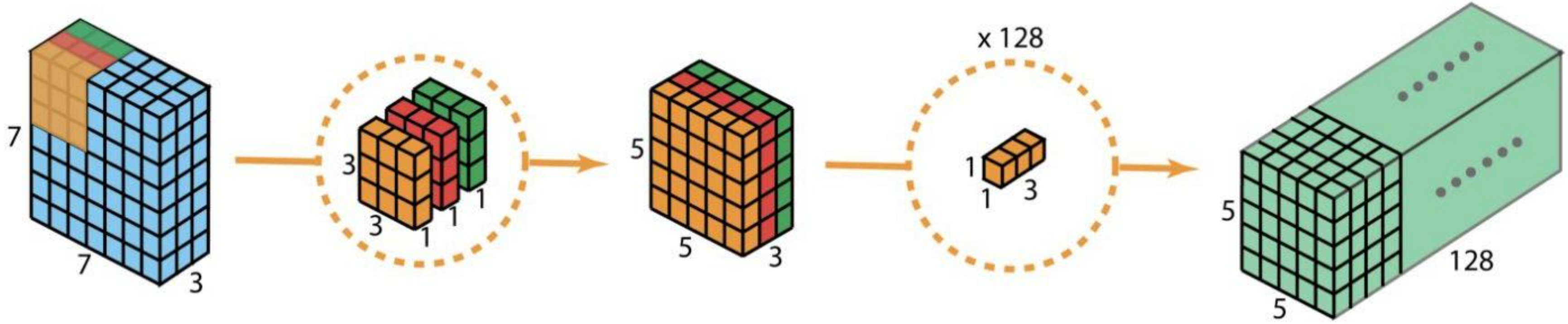
- Considering all output channels

Depth-wise Convolutions

- Shorthand for “Depth-wise separable convolutions”
- “Depth”-wise separable, because considering channels as “depth”, perform convolutions on them **independently**



Depth-wise Convolutions (Another Diagram)



Point-wise Convolutions

- "Point"-wise convolutions because **each pixel is considered independently**
- Considering just a single output channel:

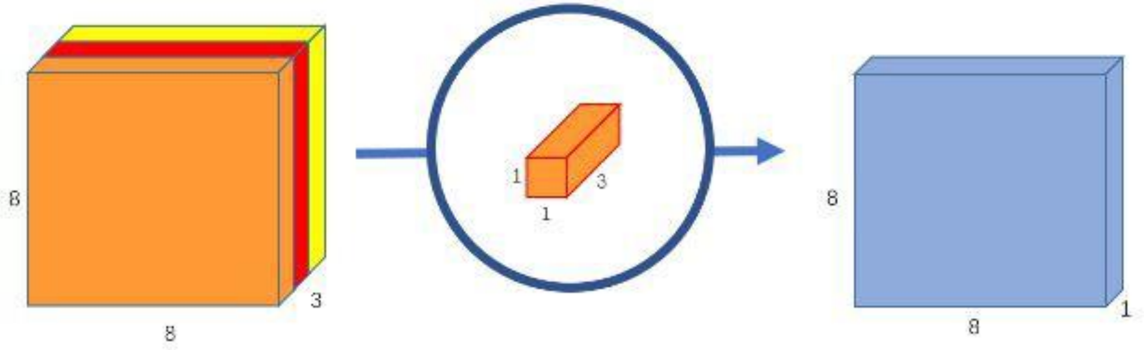


Image 7: Pointwise convolution, transforms an image of 3 channels to an image of 1 channel

Point-wise Convolutions

- “Point”-wise convolutions because **each pixel is considered independently**
- Considering all output channels:

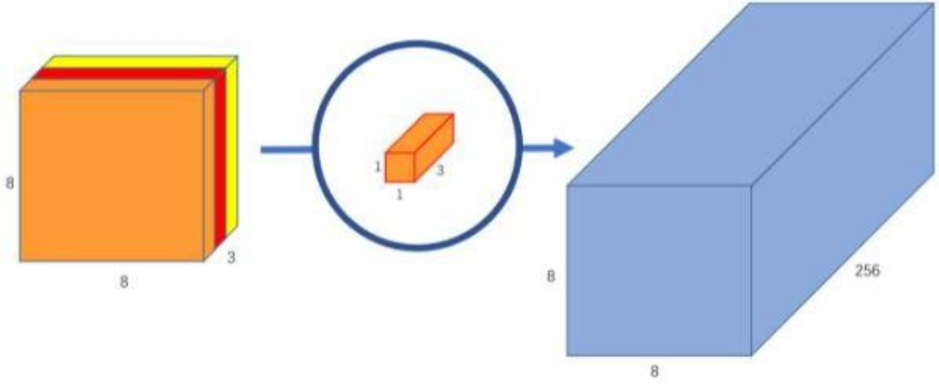


Image 8: Pointwise convolution with 256 kernels, outputting an image with 256 channels

Summary

- A normal convolution mixes information from both **different channels and different spatial locations (pixels)**
- A depth-wise convolution only mixes information **over spatial locations**
  - Different channels do not interact.
- A point-wise convolution only mixes information **over different channels**
  - Different spatial locations do not interact

Mobile Block

- Again, to understand an architecture, we mostly need to understand its **blocks**.
- All that changes for blocks in different stages is the base # of channels

Mobile Block

- The core block has three steps:
  - Feature Mixing
  - Spatial Mixing
  - Bottlenecking Channels

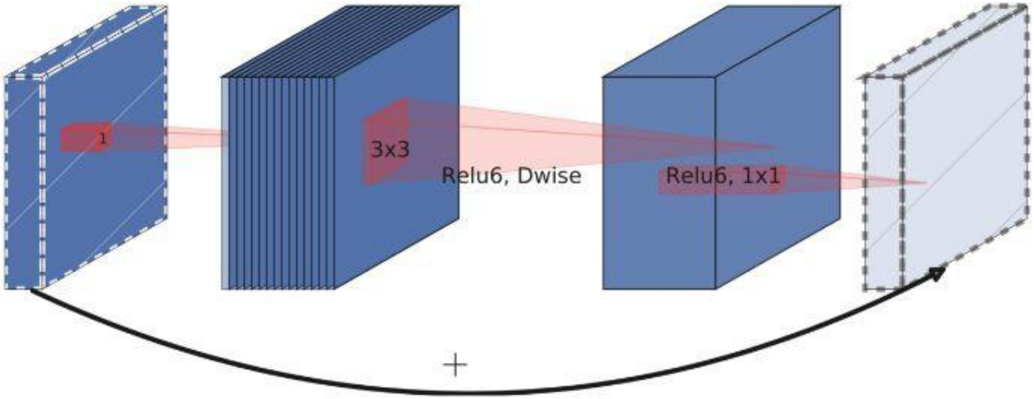


Fig. 6: Visualization of the intermediate feature maps in the inverted residual layer (source)

Mobile Block: Feature Mixing

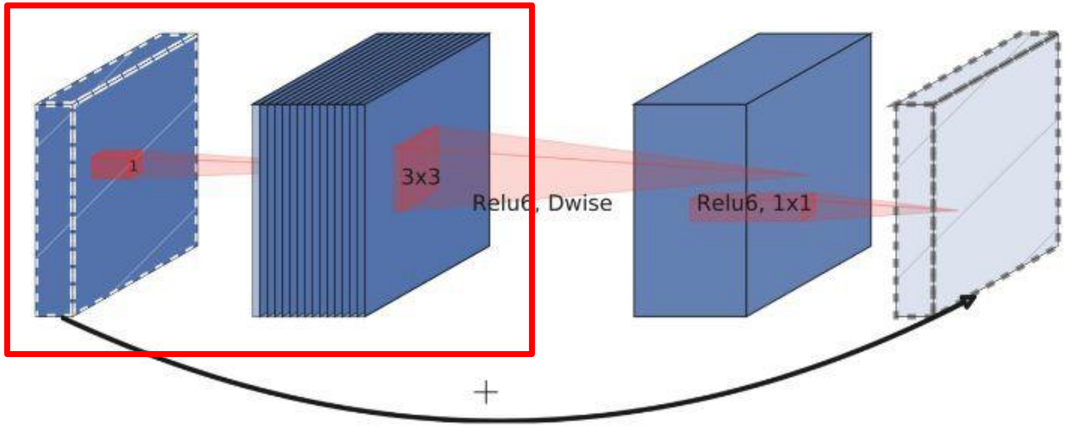


Fig. 6: Visualization of the intermediate feature maps in the inverted residual layer (source)

- A point-wise convolution that *increases the channel dimension* by an "expansion ratio"

Mobile Block: Spatial Mixing

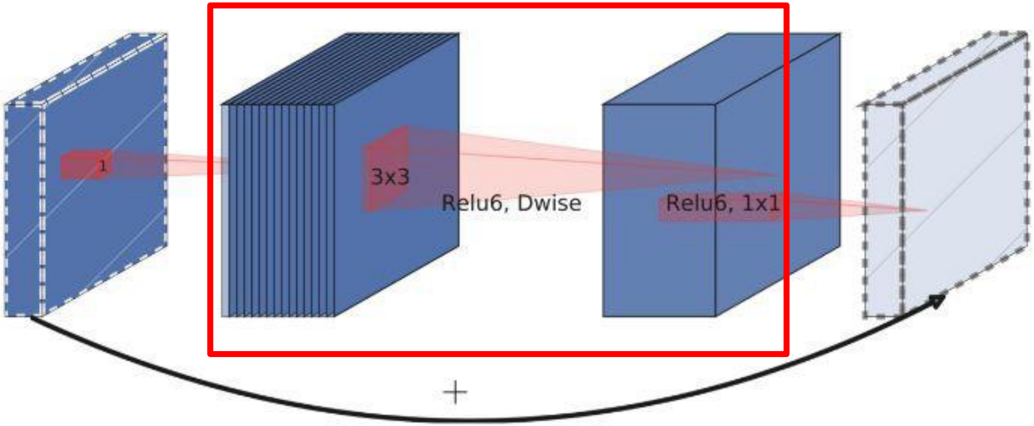


Fig. 6: Visualization of the intermediate feature maps in the inverted residual layer (source)

- A depth-wise convolution that communicates information over different spatial locations.

Mobile Block: Bottlenecking Channels

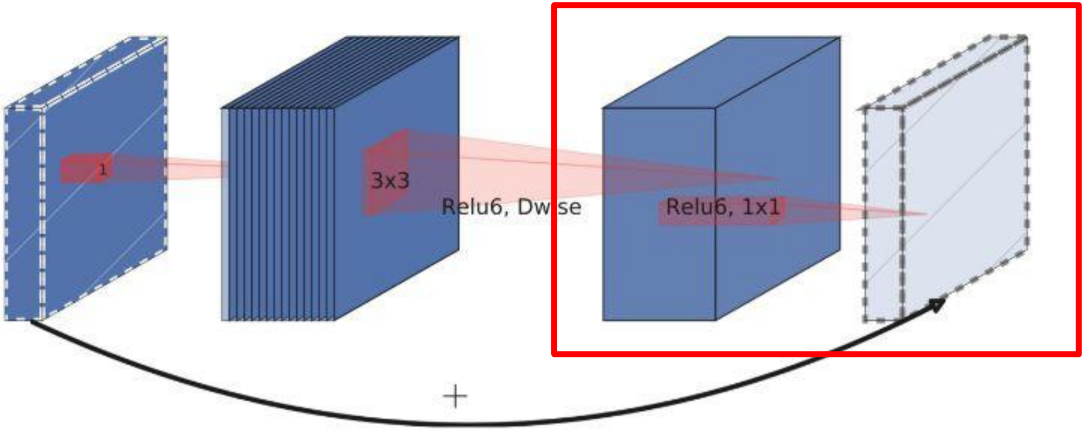


Fig. 6: Visualization of the intermediate feature maps in the inverted residual layer (source)

- Point-wise convolution to reduce channel dimension by the same expansion ratio.

ConvNeXt vs MobileNetV2

ConvNeXt

- A 7x7 depth-wise convolution.
- A point-wise convolution increasing # of channels
- A point-wise convolution decreasing # of channels
- Residual Connection

MobileNetV2

- A point-wise convolution increasing # of channels
- A 3x3 depth-wise convolution.
- A point-wise convolution decreasing # of channels
- Residual Connection

ConvNeXt vs MobileNetV2

ConvNeXt

- A 7x7 depth-wise convolution.
- A point-wise convolution increasing # of channels
- A point-wise convolution decreasing # of channels
- Residual Connection

Spatial Mixing

MobileNetV2

- A point-wise convolution increasing # of channels
- A 3x3 depth-wise convolution.
- A point-wise convolution decreasing # of channels
- Residual Connection

ConvNeXt vs MobileNetV2

ConvNeXt

- A 7x7 depth-wise convolution.
- A point-wise convolution increasing # of channels
- A point-wise convolution decreasing # of channels
- Residual Connection

Feature Mixing

MobileNetV2

- A point-wise convolution increasing # of channels
- A 3x3 depth-wise convolution.
- A point-wise convolution decreasing # of channels
- Residual Connection

ConvNeXt vs MobileNetV2

ConvNeXt

- A 7x7 depth-wise convolution.
- A point-wise convolution increasing # of channels
- A point-wise convolution decreasing # of channels
- Residual Connection

MobileNetV2

- A point-wise convolution increasing # of channels
- A 3x3 depth-wise convolution.
- A point-wise convolution decreasing # of channels
- Residual Connection

Extremely Similar!

ConvNeXt vs MobileNetV2: Differences

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  - In MobileNetV2, operates on higher # of channels.
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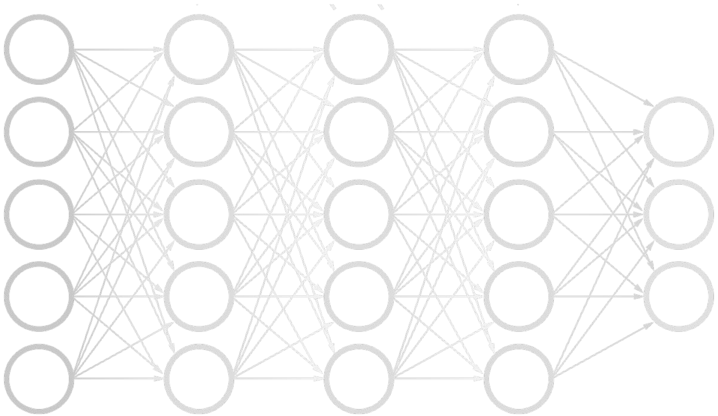
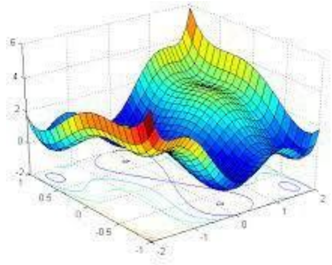
  - In MobileNetV2, operates on higher # of channels.
- Channel Expansion Ratio in ConvNeXt is 4, MobileNetV2 is 6.
- ConvNeXt uses LayerNorm, MobileNetV2 uses BatchNorm.
  - **Note: You will need to normalize the data if you use LN.**
- ConvNeXt recommends training via AdamW, MobileNetV2 recommends SGD

Other Interesting Paper

- ResNeXt (2016)
  - https://arxiv.org/pdf/1611.05431.pdf
  - Generally a strict improvement to ResNet, but slower. It's like 3 lines of code changed.
- SENet (2017)
  - https://arxiv.org/pdf/1709.01507.pdf
  - Channel-wise attention in CNNs. It's like 20 lines of code.
- EfficientNet (2019)
  - https://arxiv.org/pdf/1905.11946.pdf
  - Optimized model scaling. Probably can hard code this with some effort.
- RegNet (2020)
  - https://arxiv.org/pdf/2003.13678.pdf
  - ResNet with optimized layer sizes. It's probably… 10 lines changed?
- ResNeSt (2020)
  - https://arxiv.org/pdf/2004.08955.pdf
  - ResNeXt on steroids + attention. I (we?) will be really impressed ☺
- NFNet (2021, ~~SOTA~~) **Former SOTA**
  - https://arxiv.org/pdf/2102.06171v1.pdf
  - Quite doable actually

Building Blocks





Input Image + Transformation
s

Choice of Model

Training the model

The easy bit first….

Monitoring Training vs Validation Acc

- The standard intuition of “overfitting” is – if the training & validation gap is too large, you should stop training as it’s overfitting.
- However, in modern DL, this intuition is not as relevant.
- XELoss != Accuracy
  - Model can keep improving after training accuracy hits 100%.
  - There is recent research that finds that on some problems, training accuracy hits 100% at epoch 10 while validation accuracy is <50%. Then, on epoch 1000,
    validation hits 100%.
- Of course, we can’t train for that long, but train until validation stops improving.
  - Or just set a standard LR schedule/setup like “CosineAnnealingLR for 50 epochs” and just let it run. □ what I prefer to do.

How to tackle overfitting?

- There are *a lot* of different tricks to improving your CNN model.
- From the recent ConvNeXt paper:

(pre-)training config	ConvNeXt-T/S/B/L ImageNet-1K 224^2
optimizer	AdamW
base learning rate	4e-3
weight decay	0.05
optimizer momentum	$\beta_1, \beta_2{=}0.9, 0.999$
batch size	4096
training epochs	300
learning rate schedule	cosine decay
warmup epochs	20
warmup schedule	linear
layer-wise lr decay [6, 10]	None
randaugment [12]	(9, 0.5)
label smoothing [65]	0.1
mixup [85]	0.8
cutmix [84]	1.0
stochastic depth [34]	0.1/0.4/0.5/0.5
layer scale [69]	1e-6
gradient clip	None
exp. mov. avg. (EMA) [48]	0.9999

How to tackle overfitting?

- There are *a lot* of different trick to improving your CNN model.
- From the recent ConvNeXt paper
- What we recommend trying first:
  - Label Smoothing (huge boost)
  - Stochastic Depth
  - DropBlock (paper)
  - Dropout before final classification layer
- Then you can try the others
- Check out “Bag of Tricks for Image Classification with Convolutional Neural Networks”
  - https://arxiv.org/abs/1812.01187

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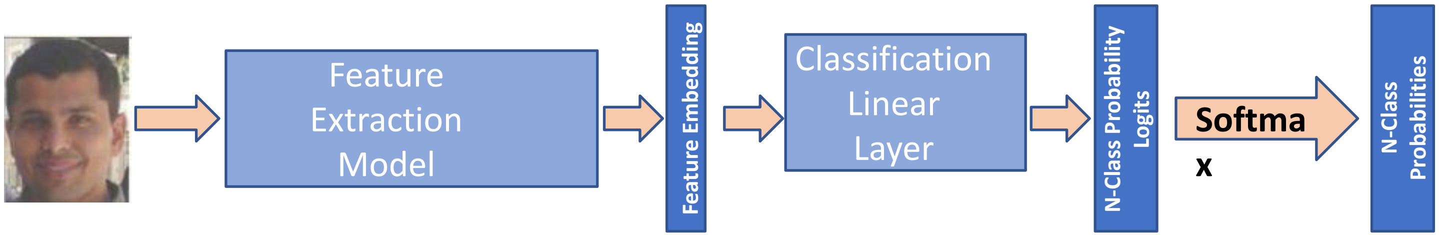
Let’s get real now….

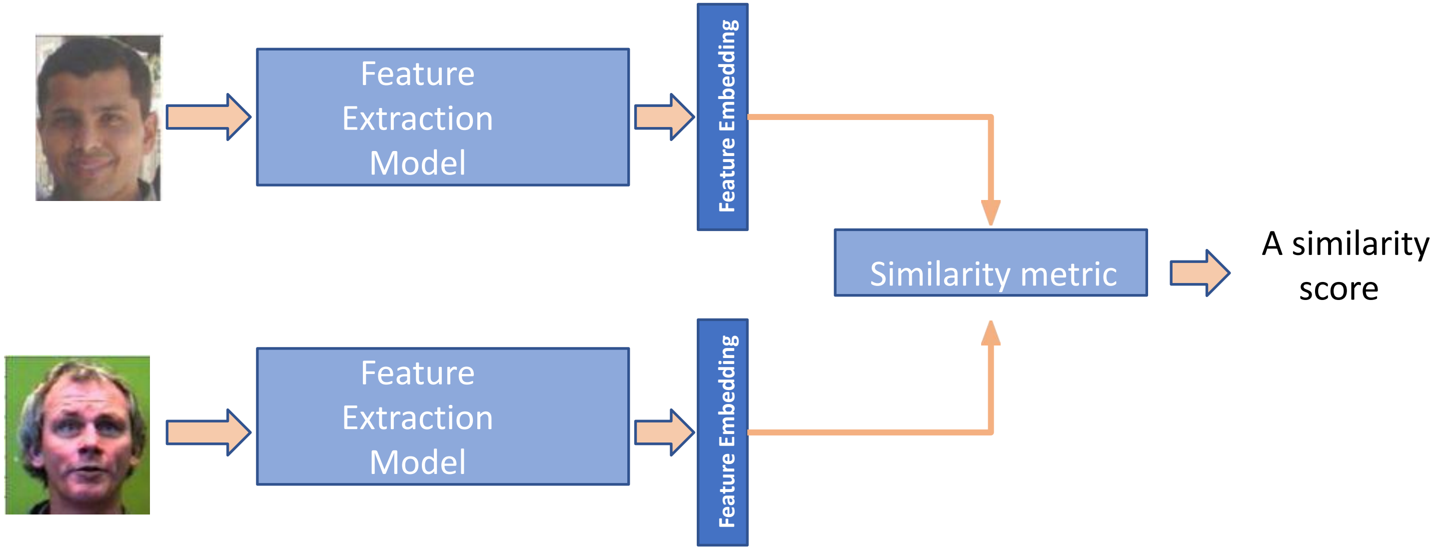
Loss Functions

Face Verification + Face Recognition tasks (VGG Face2)

Face Classification

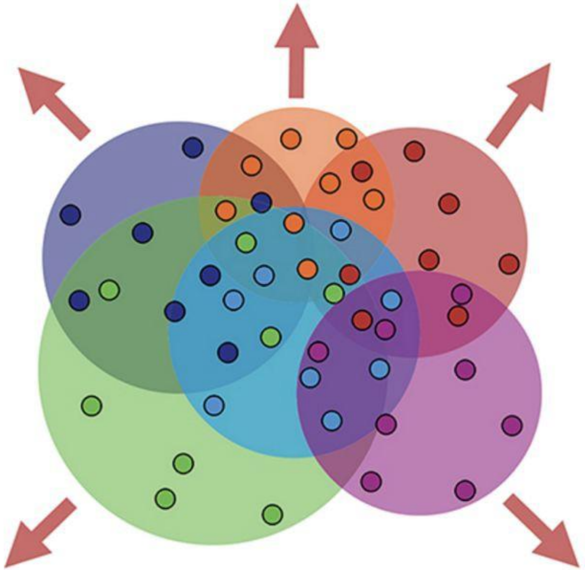


Face Verification

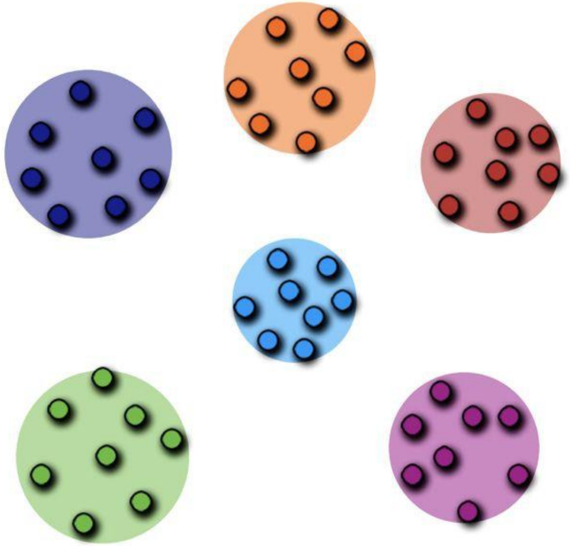


Types of Loss functions

Non Contrastive loss functions



Contrastive-Losses



Types of Loss functions

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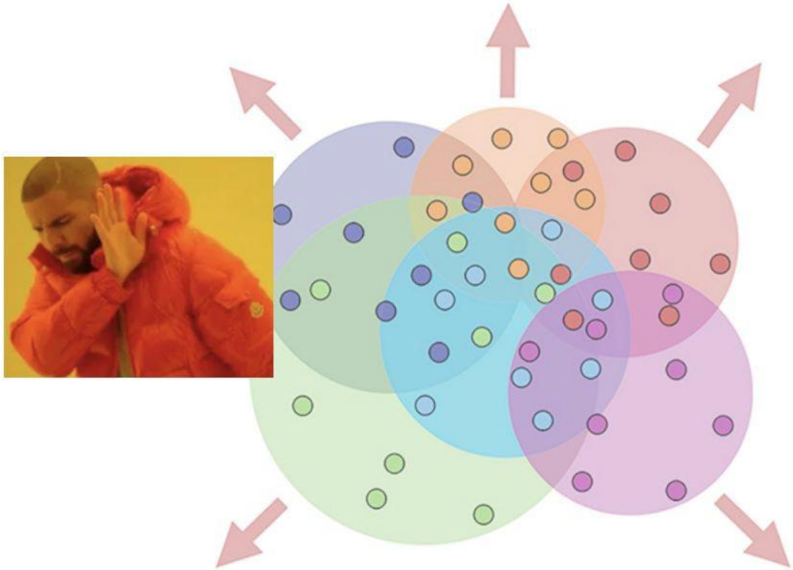
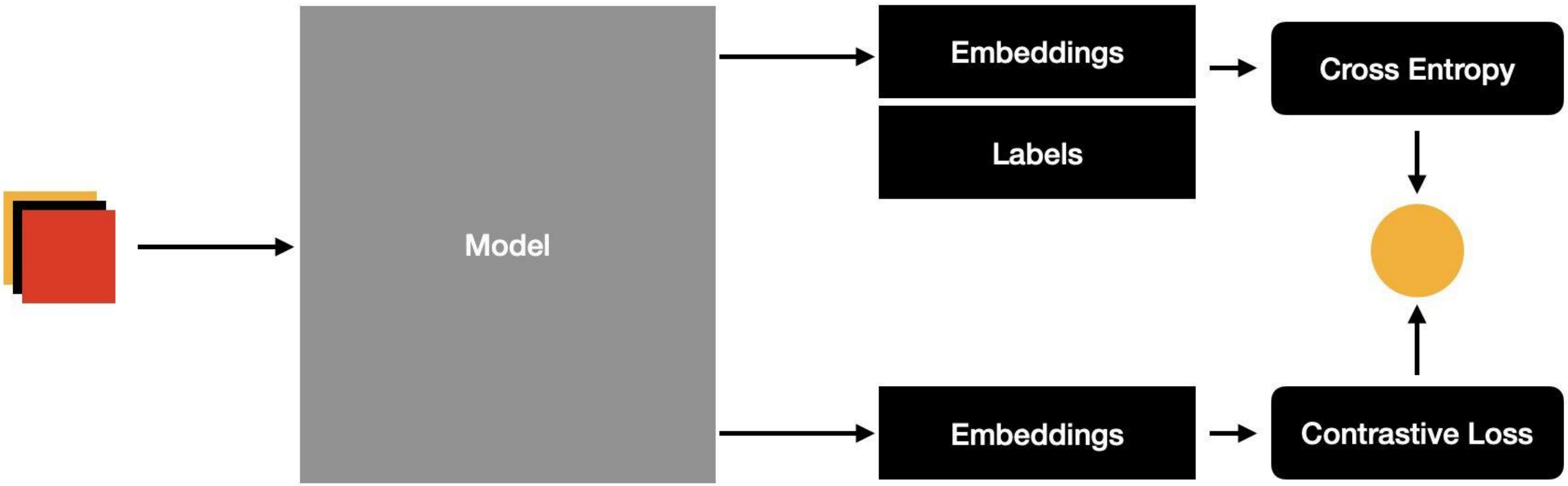


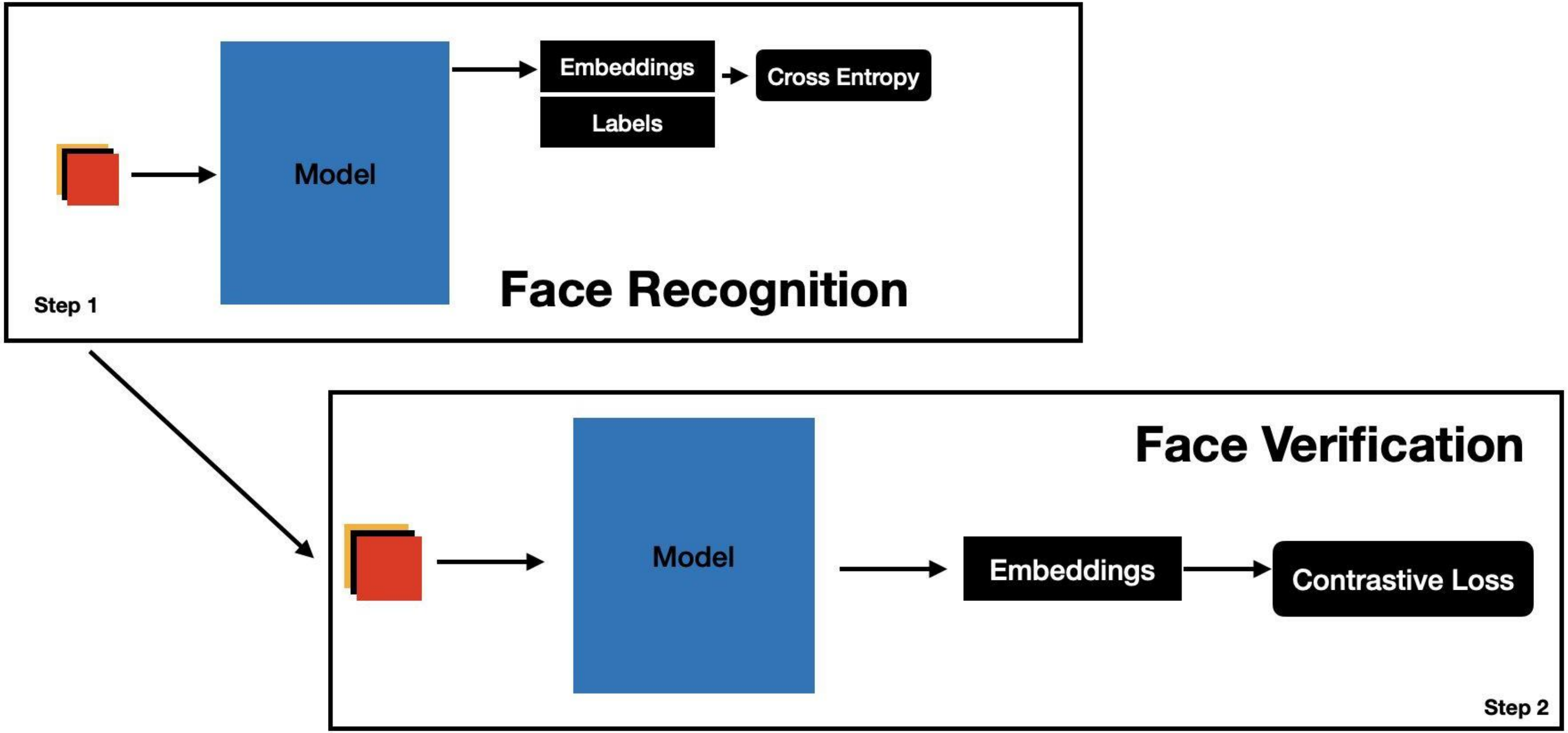
Contrastive-Losses

How to train models with such loss functions ?

Approach 1 - Joint Loss Optimization



Approach 2 - Sequential (Fine-tuning)



Types of Contrastive Losses

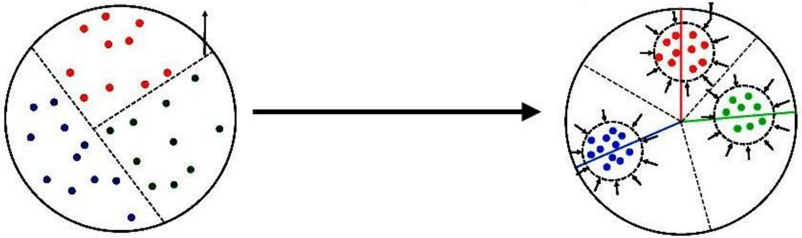
1. Centre Loss
2. Triplet Loss
3. Sphere Face (Angular Softmax)
4. CosFace Loss
5. ArcFace

Centre Loss

$$\mathcal{L}_C = \frac{1}{2}\sum_{i=1}^{m}\|\boldsymbol{x}_i - \boldsymbol{c}_{y_i}\|_2^2$$

- Increases the disparity between classes using softmax
- Increases inter-class distance by reducing intra-class Euclidean distance by assigning centers to each class.

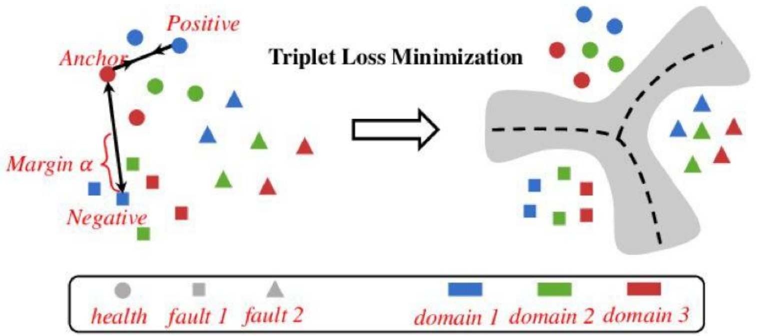
- Calculating the centre for each class, is difficult



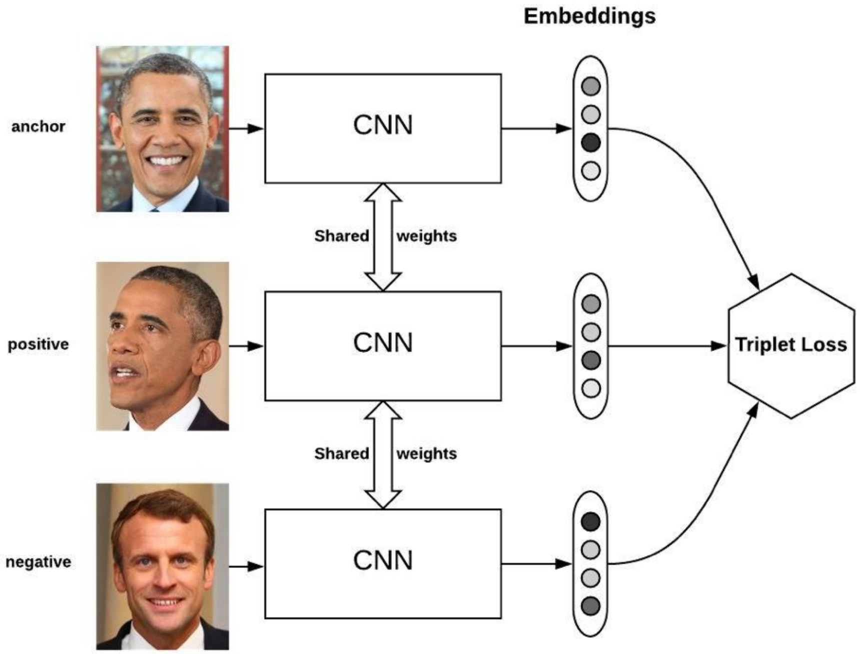
Triplet Loss

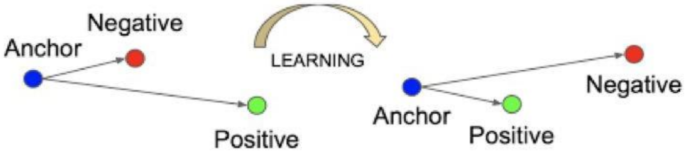
$$Loss = \sum_{i=1}^{N} \left[\|f_i^a - f_i^p\|_2^2 - \|f_i^a - f_i^n\|_2^2 + \alpha \right]_+$$

- Involves sampling 3 images, an anchor, a positive (same class as anchor) and a negative (different class from anchor).
- Use a p-norm distance function to increase the difference between anchor and negative whilst minimizing distance between anchor and positive.
- Sampling hard positives and hard negatives is key and difficult



Triplet Loss



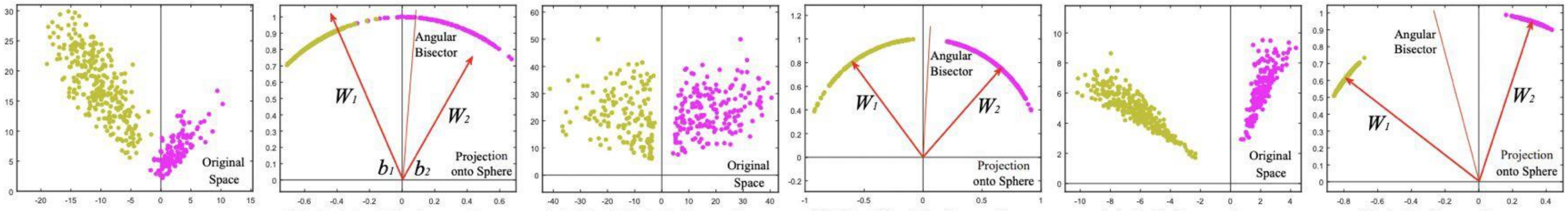


Sphere Face

$$L_{\text{ang}} = -\sum_i \ln \frac{\exp\left\{\|\mathbf{x_i}\| \cos(m \cdot \theta_{y_i,i})\right\}}{\exp\left\{\|\mathbf{x_i}\| \cos(m \cdot \theta_{y_i,i})\right\} + \sum_{j \neq y_i} \exp\left\{\|\mathbf{x_i}\| \cos\left(\theta_{j,i}\right)\right\}}$$

- **Makes use of an angular margin, imposed by θ**
- **The learned features construct a discriminative angular distance equivalent to the geodesic distance on a hypersphere manifold**

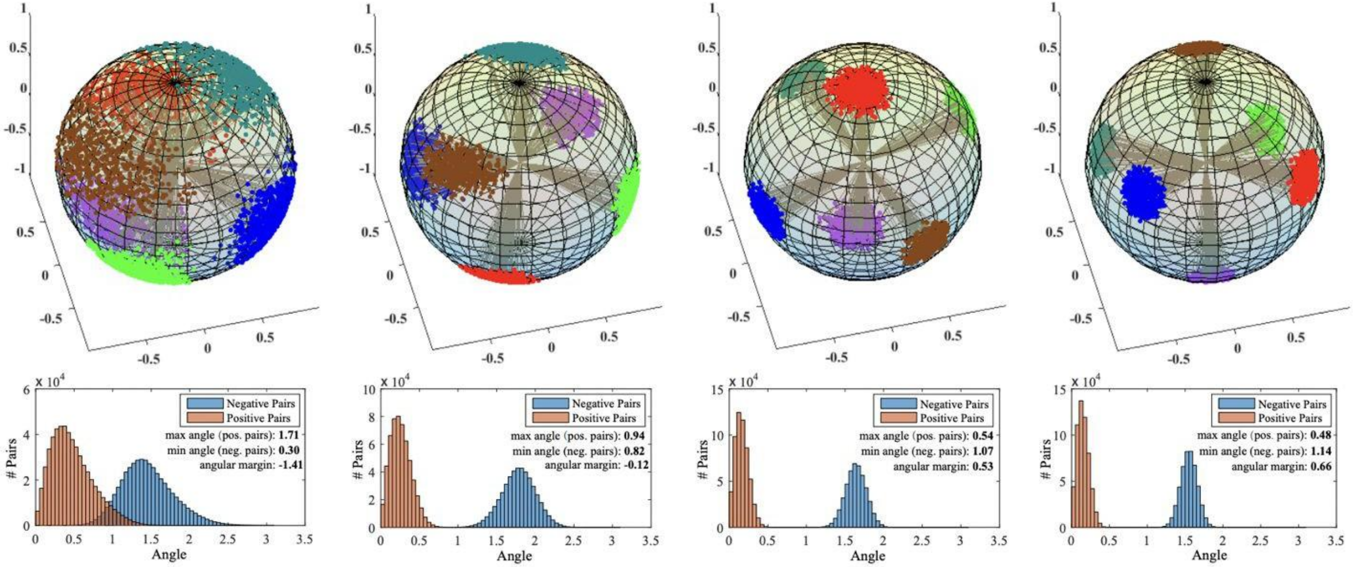
- **θ :- denotes the type of decision boundary learned, which leads to different margins for different classes**



(a) Original Softmax Loss (b) Original Softmax Loss (c) Modified Softmax Loss (d) Modified Softmax Loss (e) A-Softmax Loss (f) A-Softmax Loss

Sphere Face

M ∝ Angular Margin

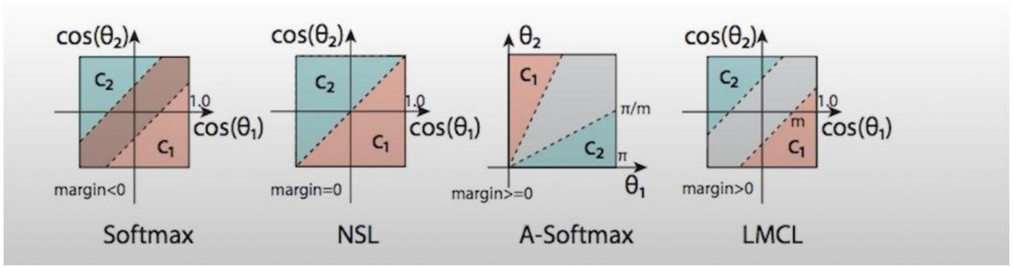


A-Softmax (m=1) A-Softmax (m=2) A-Softmax (m=3) A-Softmax (m=4)

CosFace

$$L_{\mathrm{lmc}} = -\frac{1}{N}\sum_{i=1}^{N} \ln \frac{\exp\left\{s \cdot \left(\cos\left(\theta_{y_i,i}\right) - m\right)\right\}}{\exp\left\{s \cdot \left(\cos\left(\theta_{y_i,i}\right) - m\right)\right\} + \sum_{j \neq y_i} \exp\left\{s \cdot \left(\cos(\theta_{j,i})\right)\right\}}$$

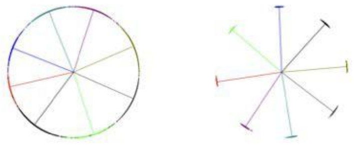
- **Similar to Sphere Face**
- **Forms the decision margin in cosine space rather than angular space.**



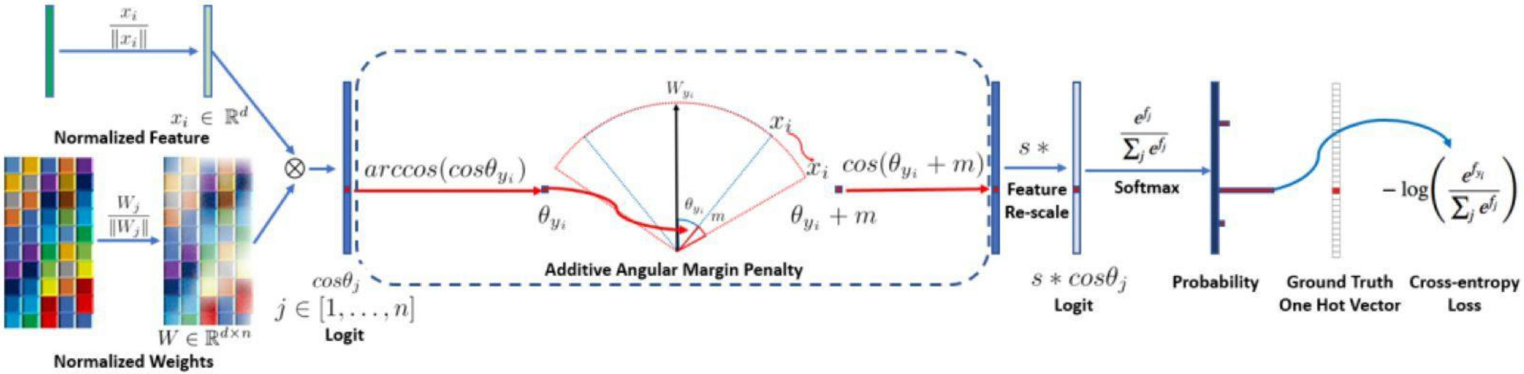
ArcFace

$$L = -\frac{1}{N}\sum_{i=1}^{N}\ln\frac{\exp\left\{s\cdot\cos(\theta_{y_i,i}+m)\right\}}{\exp\left\{s\cdot\cos\left(\theta_{y_i,i}+m\right)\right\}+\sum_{j\neq y_i}\exp\left\{s\cdot(\cos(\theta_{j,i})\right\}}$$

- **Builds on the concepts of the sphere face and cos face.**
- **Replaced the multiplicative angular margin in CosFace, with an additive margin 'm'**



(a) Norm-Softmax (b) ArcFace



ArcFace

- The additive factor of ‘m’ has found to lead to better convergence as compared to its multiplicative counterpart in Sphere Face.

CMU Virtual Andrew

https://www.cmu.edu/computing/services/endpoint/software/virtual-andrew.html