

Recent CNN Architectures

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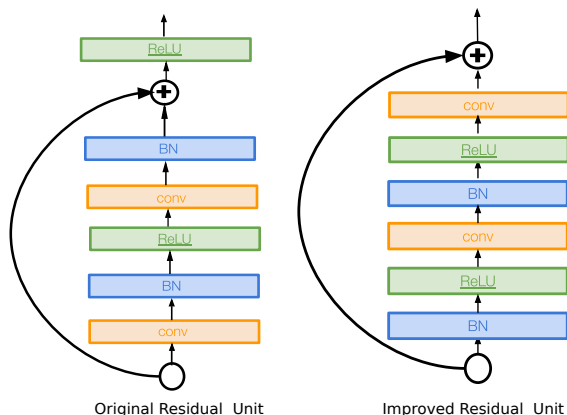
Recent CNN Architectures

We have already seen some deep convolutional architectures, including a very deep network that uses residual connections. Here we consider some other recent CNN architectures:

- Wide Residual Networks (WideResNet)
- Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)
- Deep Networks with Stochastic Depth
- Densely Connected Convolutional Networks (DenseNets)
- More recent: MobileNet, EfficientNet, SEnet

Identity Mappings in Deep Residual Networks¹

- Improved ResNet block design from creators of ResNet
- Switches up order of activations in the residual block
- Creates a more direct path for propagating information through the network
- Gives better performance

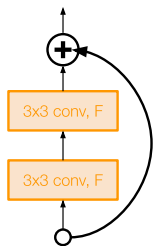


Credit: Fei-Fei Li, CS231n, Stanford Univ

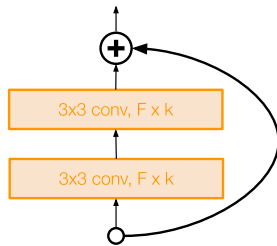
¹He et al, Identity Mappings in Deep Residual Networks, ECCV 2016

Wide Residual Networks²

- Builds on ResNets
- Argues that residuals are the important factor and not depth
- Uses wider residual blocks ($F \times k$ filters instead of F filters in each layer)
- 50-layer WideResNet outperforms 152-layer original ResNet
- Increasing width instead of depth computationally more efficient (parallelizable)



Basic residual block



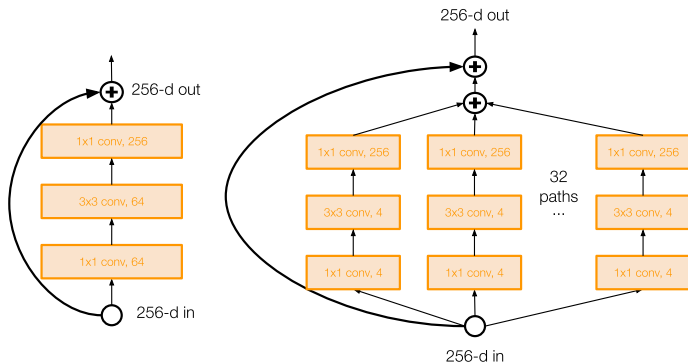
Wide residual block

Credit: Fei-Fei Li, CS231n, Stanford Univ

²Zagoruyko and Komodakis, Wide Residual Networks, BMVC 2016

Aggregated Residual Transformations (ResNeXt)³

- Also from creators of ResNet
- Increases width of residual block through multiple parallel pathways (called **cardinality**)
- Parallel pathways similar in spirit to Inception module



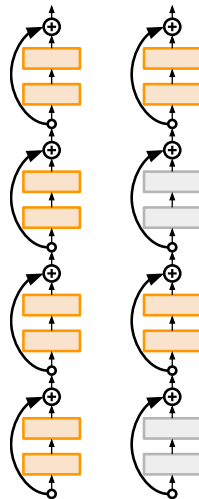
Credit: Fei-Fei Li, CS231n, Stanford Univ

³Xie et al, Aggregated Residual Transformations for Deep Neural Networks, CVPR 2017

Deep Networks with Stochastic Depth⁴

- Think DropOut of residual blocks!
- Randomly drop a subset of layers during each training pass
- Bypass with identity function
- **Motivation:** Reduce vanishing gradients and training time through short networks during training, also an added regularizer
- Use full deep network at test time

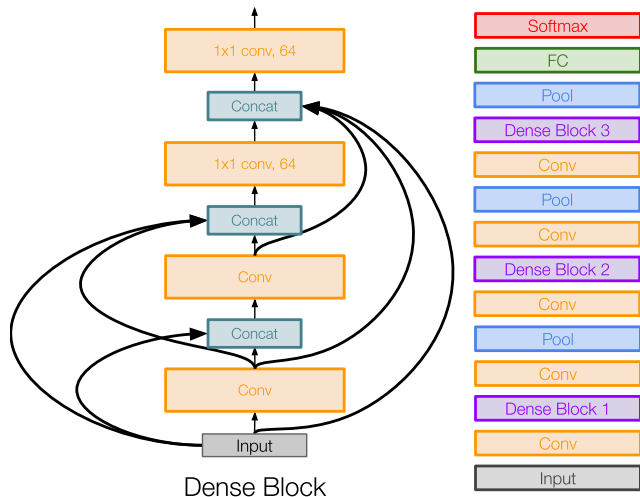
Credit: Fei-Fei Li, CS231n, Stanford Univ



⁴Huang et al, Deep Networks with Stochastic Depth, ECCV 2016

Densely Connected Convolutional Networks (DenseNets)⁵

- **Dense blocks** where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse
- Showed that shallow 50-layer network can outperform deeper 152-layer ResNet
- Quite popularly in use today for image classification problems



⁵Huang et al, Densely Connected Convolutional Networks, CVPR 2017

MobileNets: Efficient Convolutional Neural Networks for Mobile Applications⁶

- A class of efficient models for mobile and embedded vision applications
- What are desirable properties of a network for use in small devices?

⁶Howard et al, MobileNets: Efficient Convolutional Neural Networks for Mobile Applications, 2017

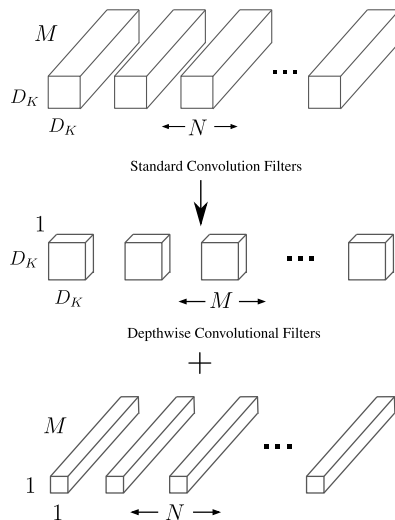
MobileNets: Efficient Convolutional Neural Networks for Mobile Applications⁶

- A class of efficient models for mobile and embedded vision applications
- What are desirable properties of a network for use in small devices?
 - Low latency
 - Low power consumption
 - Small model size (devices are low memory)
 - Sufficiently high accuracy
- **MobileNets** are small, low latency networks which are trained directly. A complementary approach to building efficient networks is compressing pre-trained networks.

⁶Howard et al, MobileNets: Efficient Convolutional Neural Networks for Mobile Applications, 2017

Key Ingredient: Depthwise Separable Convolutions

- MobileNets primarily built using **depthwise separable convolutions (DSC)**
- DSC replaces standard convolutions with depthwise convolution and 1×1 convolution
- DSC applies a single filter to each input channel; **how does this help over normal convolution?**



Depthwise Separable Convolutions

- Let input have size $D_f \times D_f \times M$ and output feature map (after passing input through conv layer) has $D_f \times D_f \times N$ size. Assume padded convolution. Let width of the square kernel in conv layer be k

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Depthwise Separable Convolutions

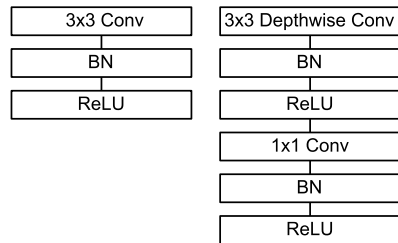
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- A standard convolutional layer would have $k \times k \times M \times N$ parameters and a computational cost of $k \cdot k \cdot M \cdot N \cdot D_f \cdot D_f$
- A depthwise separable conv layer factorizes the above into:
 - Depthwise convolutions**, having $k \times k \times M$ parameters and a cost of $k \cdot k \cdot M \cdot D_f \cdot D_f$.
 - Pointwise convolutions**, having $1 \times 1 \times M \times N$ parameters and cost of $M \cdot N \cdot D_f \cdot D_f$.
- By what fraction is computation reduced when DSC is used?

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 - Pointwise convolutions**, having $1 \times 1 \times M \times N$ parameters and cost of $M \cdot N \cdot D_f \cdot D_f$.
- By what fraction is computation reduced when DSC is used? **Homework!**
- Depthwise convolutions filter feature maps channelwise, and pointwise convolutions combine feature maps across channels; standard convolutions do these operations together

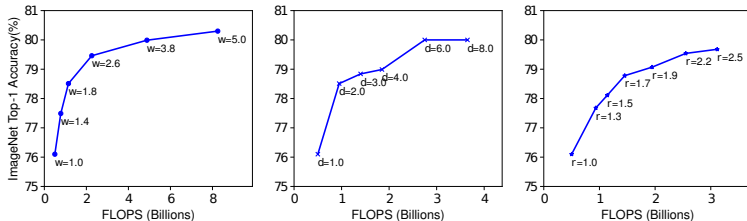
MobileNet: Architecture and Hyperparameters

- MobileNet built of many depthwise convolutions and pointwise convolutions, each of which is followed by BatchNorm and ReLU
- To obtain faster and smaller models, two more hyperparameters are considered:
 - **Width multiplier**, α , controls number of channels, making the number of input channels as αM and number of output channels as αN for all layers
 - **Resolution multiplier**, ρ , scales input image to a fraction of its size



Left: Standard conv layer with batchnorm and ReLU.
Right: Depthwise Separable convolutions with

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks⁷



Scaling up a Baseline model with different network width (**w**), depth (**d**) and input resolution (**r**). Bigged networks with larger width, height and input resolution perform better but accuracy gain saturates.

- Conventional wisdom suggests that scaling up CNN architectures would lead to better accuracy i.e deeper and wider networks perform better in general
- Explores a principled way to scale up a CNN to obtain better accuracy and efficiency

⁷Tan and Le, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks, ICML 2019

EfficientNet

- Makes two observations:
 - Scaling up any dimension (w, d, r) independently improves accuracy, but return diminishes for bigger models
 - For better accuracy, critical to balance all dimensions during scaling; Intuitively, does it make sense to have deeper and wider models for larger input dimensions?

EfficientNet

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 - Scaling up any dimension (w,d,r) independently improves accuracy, but return diminishes for bigger models
 - For better accuracy, critical to balance all dimensions during scaling; **Intuitively, does it make sense to have deeper and wider models for larger input dimensions?**
- Based on these observations, a new **compound scaling method** is proposed
- A compound coefficient ϕ uniformly scales network width, depth and resolution

depth: $d = \alpha^\phi$

width: $w = \beta^\phi$

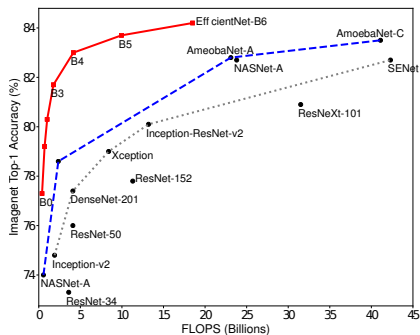
resolution: $r = \gamma^\phi$

s.t $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$

$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$

where α, β, γ are constants
determined by a small grid search

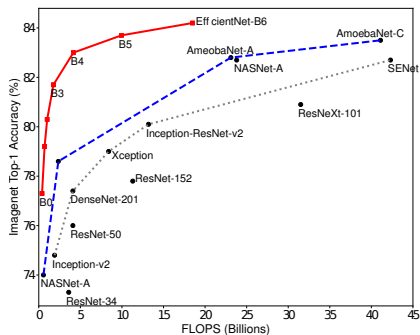
EfficientNet



FLOPS vs. ImageNet Accuracy

- For any new compound coefficient ϕ , total FLOPS will approximately increase by 2^ϕ . Why?

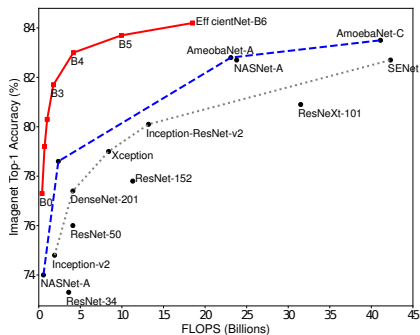
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Homework!
- Fixing $\phi = 1$ and assuming double the amount of resources, a grid search is performed on α, β, γ for chosen baseline network
- For every available computational budget, ϕ is calculated and model is scaled accordingly

EfficientNet



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- Fixing $\phi = 1$ and assuming double the amount of resources, a grid search is performed on α, β, γ for chosen baseline network
- For every available computational budget, ϕ is calculated and model is scaled accordingly
- Baseline model is obtained by performing **Neural Architecture Search** (an advanced topic we will see later in this course); scaling up this baseline leads to a family of models called EfficientNets

Squeeze-and-Excitation Networks (SENet)⁸

- **Motivation:** Improve quality of representations produced by network by explicitly modeling interdependencies between channels of its convolutional features
- Proposes a novel architectural unit termed **Squeeze-and-Excitation (SE) block**:
 - **Squeeze** operation embeds global information
 - **Excitation** operation re-calibrates feature maps channel-wise

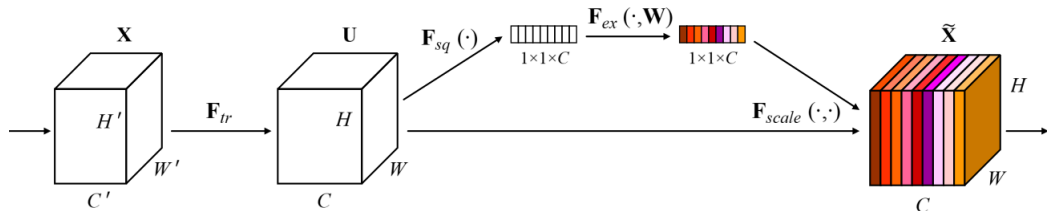
⁸Hu et al, Squeeze-and-Excitation Networks, CVPR 2018

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- If F_{tr} is a transformation mapping input $X \in \mathbb{R}^{H' \times W' \times C'}$ to output feature maps $U \in \mathbb{R}^{H \times W \times C}$, e.g. a convolution, then SE block squeezes and recalibrates U

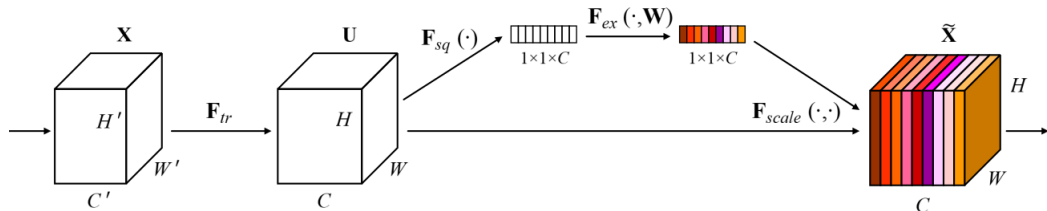
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SENet: Squeeze-and-Excitation Block



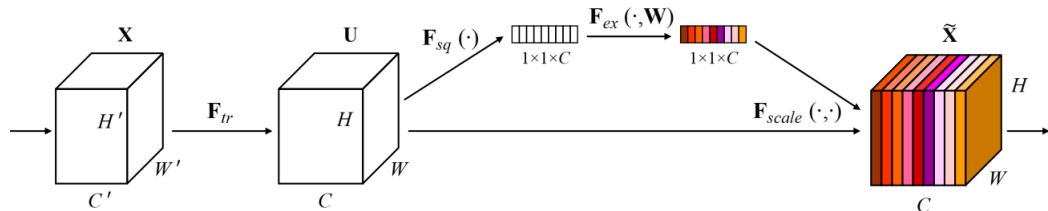
- Learns to reweigh feature maps (using global information) in a way that emphasises informative features and inhibits less useful ones.
- F_{sq} , the **squeeze function**, is channel-wise **global average pooling** - globally aggregate feature maps spatially

SENet: Squeeze-and-Excitation Block



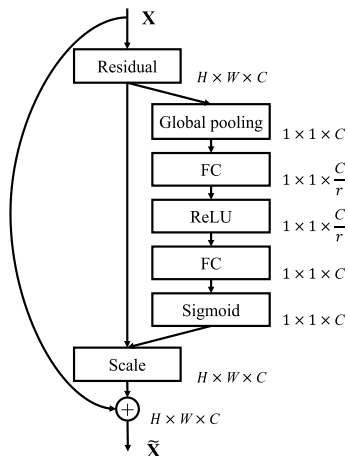
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- F_{ex} , the **excitation function**, learns the relationships between channels, and outputs channelwise activations
- F_{scale} performs channelwise multiplication of feature maps U with learned activations

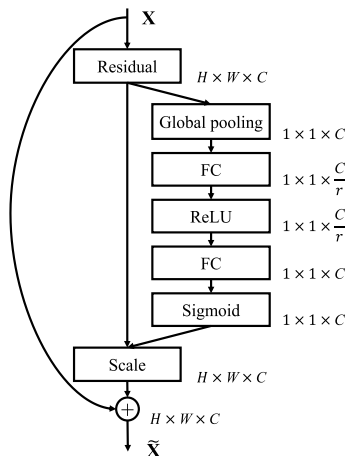
Squeeze-and-Excitation Block in ResNet



SE-ResNet Module

- r is a hyperparameter that controls size of hidden layer

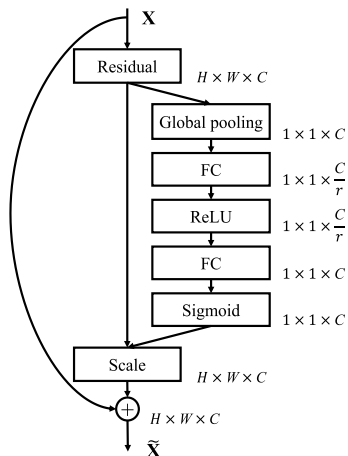
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- Output of F_{ex} is a set of C numbers between $(0, 1)$, each detailing how much attention each channel receives

Squeeze-and-Excitation Block in ResNet



SE-ResNet Module

- r is a hyperparameter that controls size of hidden layer
- Output of F_{ex} is a set of C numbers between $(0, 1)$, each detailing how much attention each channel receives
- SE block is a cheap way to increase model depth
- Can be added to a wide variety of conv architectures, not just ResNet - to bring improvements to performance at minor additional computation cost

Homework

Readings

- Lecture 9 of [CS231n, Stanford Univ](#)
- [Google AI Blog](#) on MobileNet
- (Optional) Lecture 4 of [Svetlana Lazebnik CS598 course, UIUC](#)

Exercises

- By what fraction is computation reduced when DSC is used over standard convolution? (Slide 10)
- For a compound coefficient ϕ , total FLOPS will approximately increase by 2^ϕ . Why? (Slide 14)

References I



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