EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

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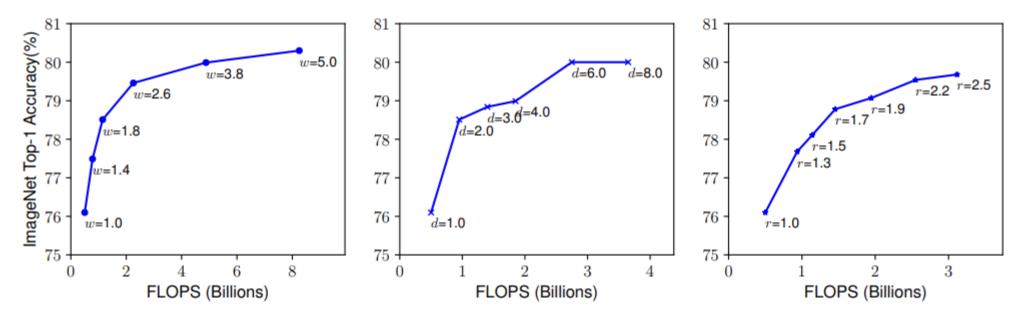
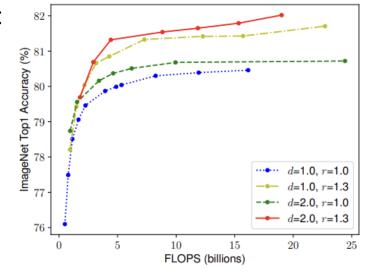


Figure 3. Scaling Up a Baseline Model with Different Network Width (w), Depth (d), and Resolution (r) Coefficients. Bigger networks with larger width, depth, or resolution tend to achieve higher accuracy, but the accuracy gain quickly saturate after reaching 80%, demonstrating the limitation of single dimension scaling. Baseline network is described in Table 1.

Scaling up one of the dimensions tend to saturate

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- 1. Scaling up one of the dimensions tend to saturate
- 2. Scaling dimensions are not independent: higher resolution requires greater depth to enlarge receptive fields, or network width Q
- → Hypothesis : need to balance different scaling dimensions
- → Experiment :



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Proposal: Compound scaling method

$$\begin{array}{l} \text{depth: } d=\alpha & \text{Hyperparameter} \\ \text{width: } w=\beta^{\phi} \\ \text{resolution: } r=\gamma^{\phi} \\ \text{s.t. } \alpha\cdot\beta^2\cdot\gamma^2\approx 2 \\ \alpha\geq 1, \beta\geq 1, \gamma\geq 1 \end{array}$$

Thoughts

Proposal: Compound scaling method

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depth: d=\alpha^{\phi} width: w=\beta^{\phi} resolution: r=\gamma^{\phi} 2 is set for the convenience of s.t. \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 estimating the amount of FLOPS \alpha \geq 1, \beta \geq 1, \gamma \geq 1 Using a different coefficient give different results?
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Nope. The range can vary same for any coefficient

Thoughts

Proposal: Compound scaling method

depth:
$$d=\alpha^{\phi}$$
 width: $w=\beta^{\phi}$ resolution: $r=\gamma^{\phi}$ s.t. $\alpha\cdot\beta^2\cdot\gamma^2\approx 2$ $\alpha\geq 1, \beta\geq 1, \gamma\geq 1$

2 is set for the convenience of estimating the amount of FLOPS

Using a different coefficient give different results?

Yes. Given that all alpha, beta and gamma is greater than 1

Architecture

Baseline Network : MnasNet?

Table 1. EfficientNet-B0 baseline network – Each row describes a stage i with \hat{L}_i layers, with input resolution $\langle \hat{H}_i, \hat{W}_i \rangle$ and output channels \hat{C}_i . Notations are adopted from equation 2.

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels \hat{C}_i	#Layers \hat{L}_i
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Building block is inverted bottleneck
MBConv from Mobilenetv2

Architecture

Application of compound scaling method

- 1. Fix theta, grid search for alpha beta gamma
- 2. Fix alpha beta gamma and scale up theta only

Room for improvement : With a larger theta, do grid search for alpha beta gamma

Architecture

Others

- 1. Applied SiLU activation
- 2. AutoAugmentation
- 3. Stochastic Depth