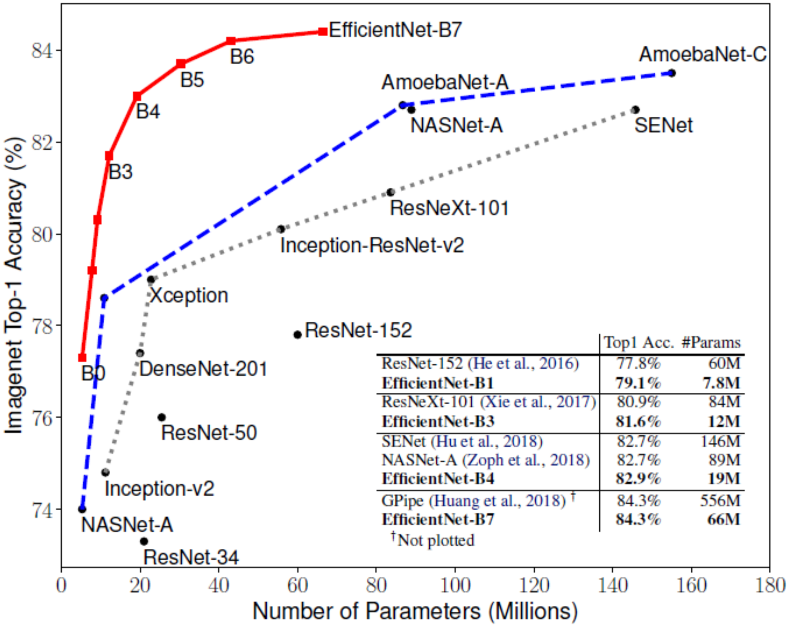
EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks



Pere Gilabert
February 2021

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1. How to scale

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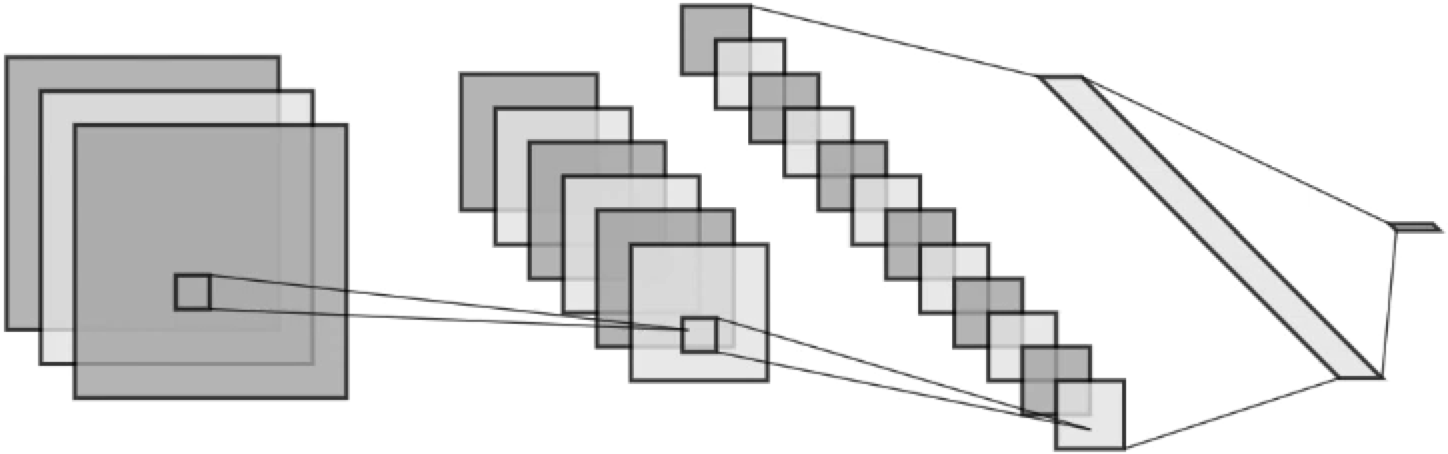

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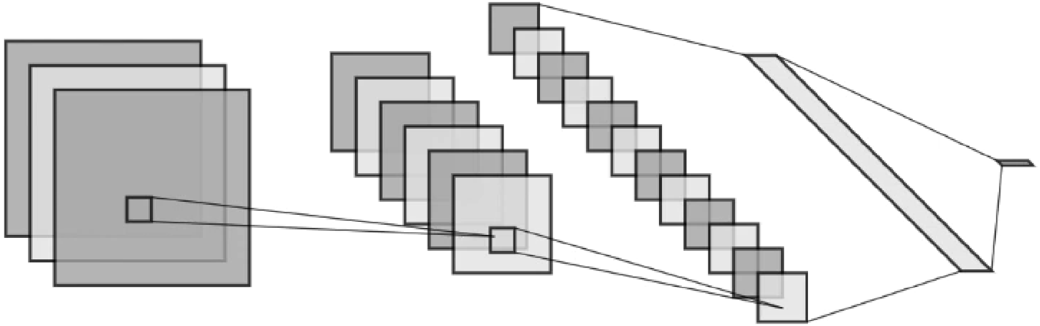
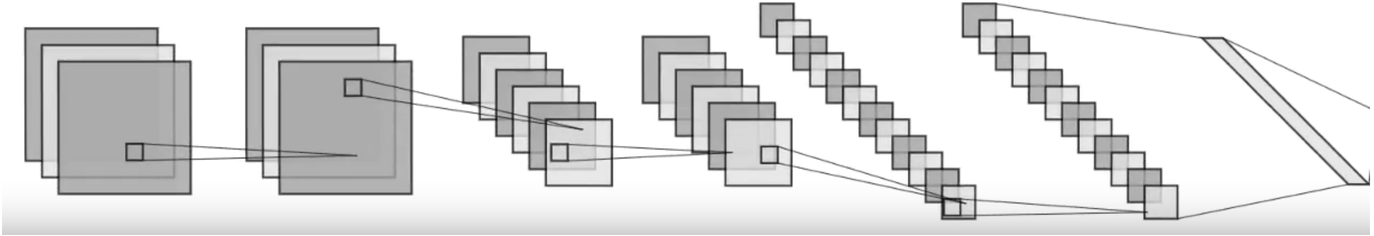


1. Add new layers



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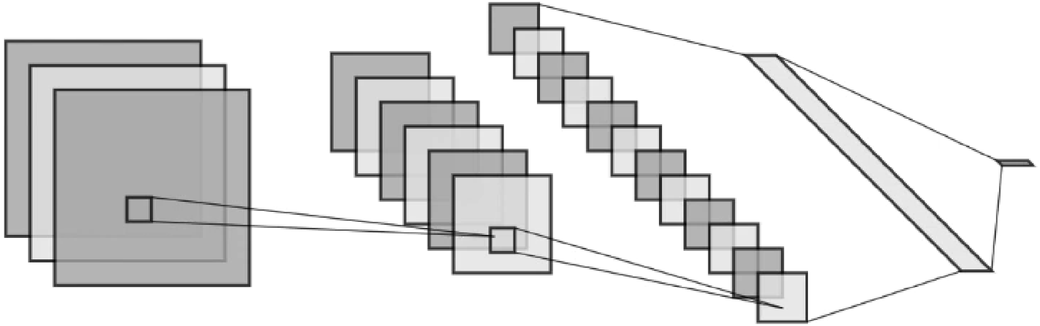

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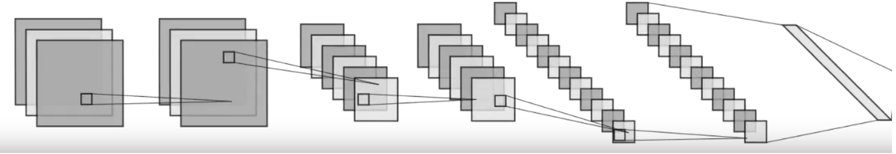
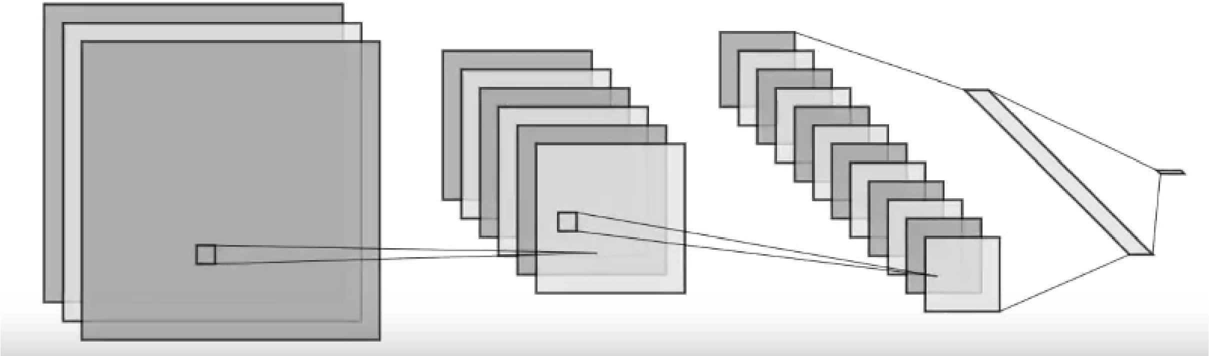


2. Increase height and width



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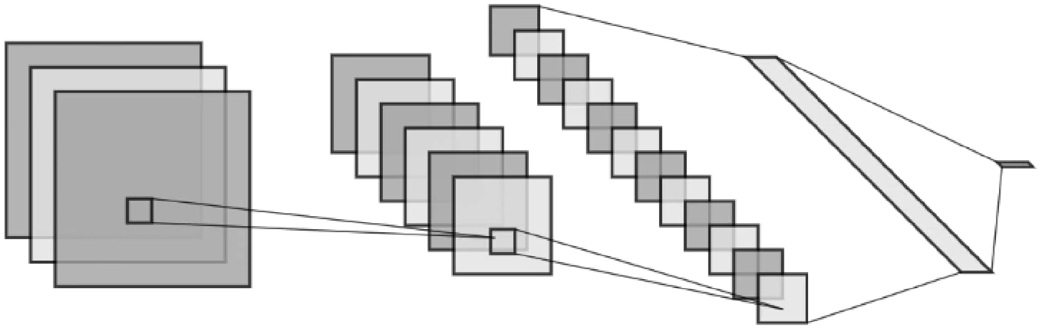

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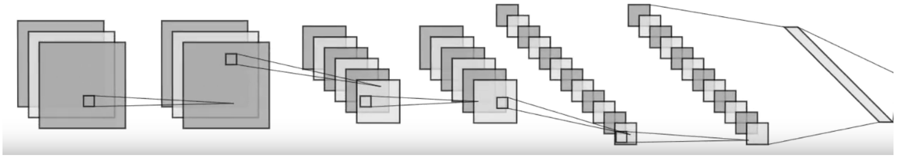

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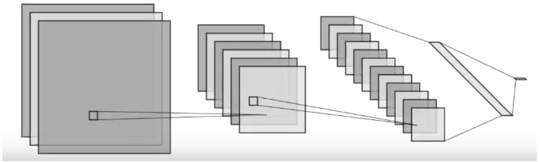
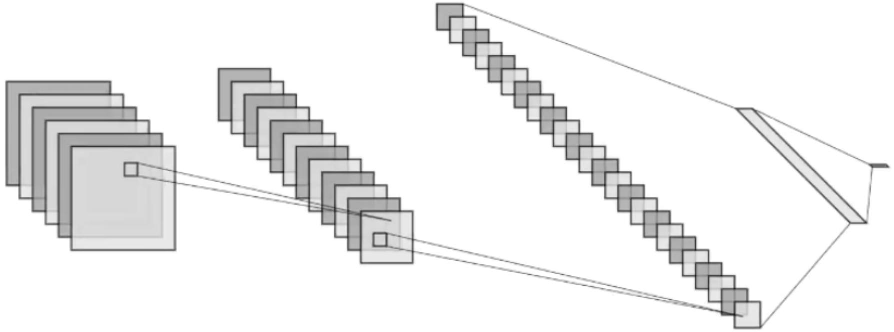


3. Increase the number of channels



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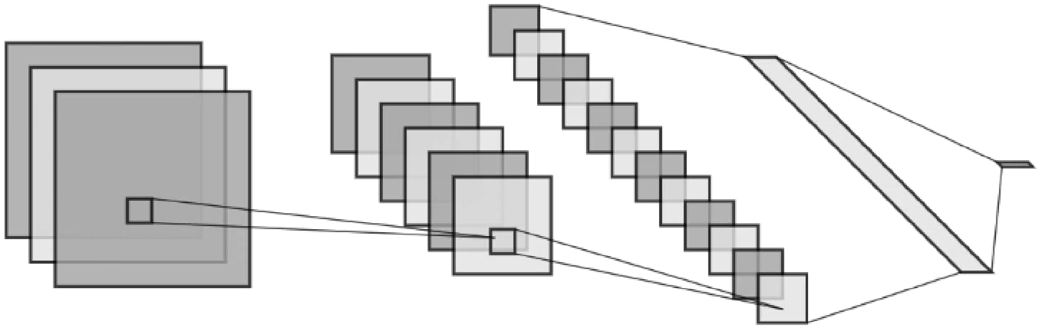
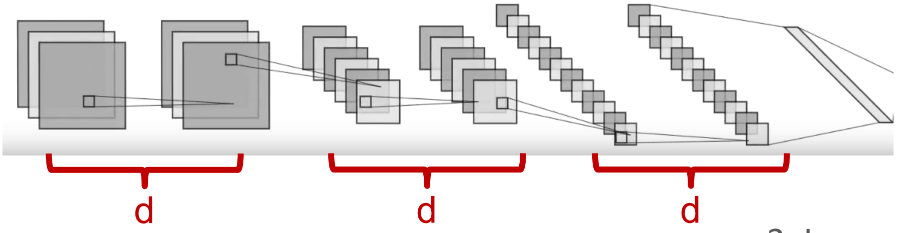
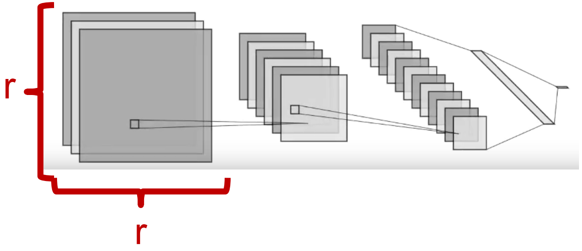


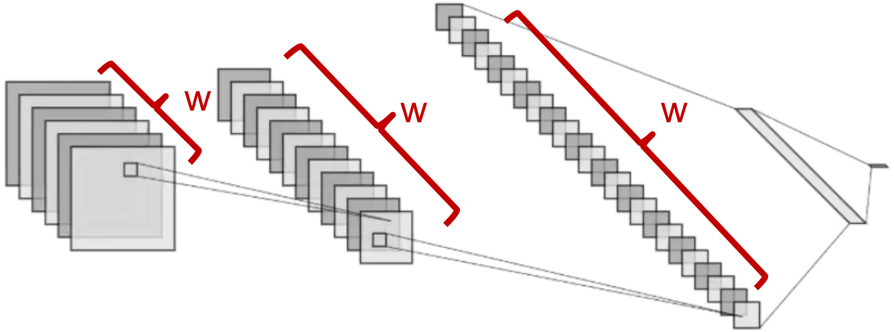
1. Add new layers **(d=2)**



2. Increase height and width **(r=2)**



3. Increase the number of channels **(w=2)**



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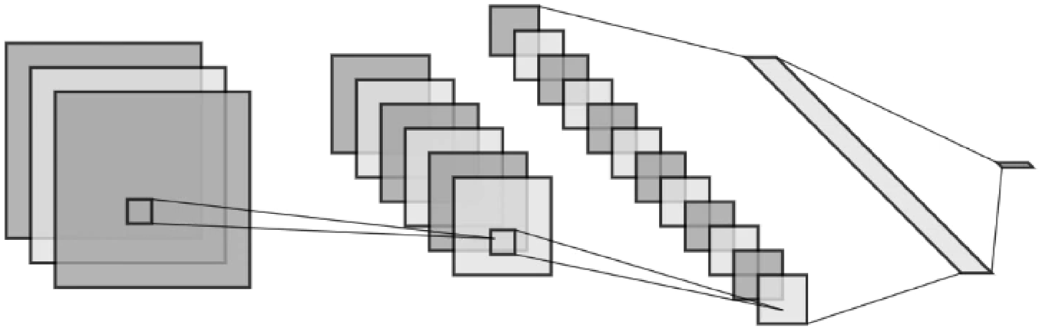

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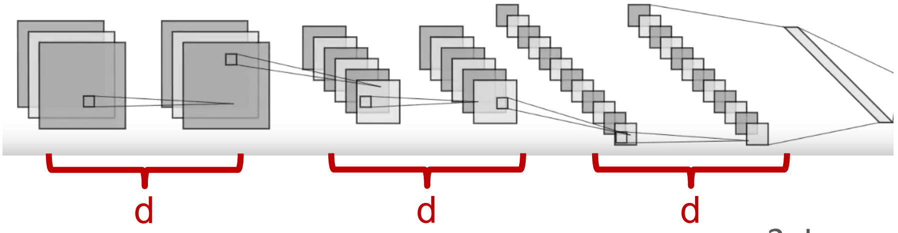
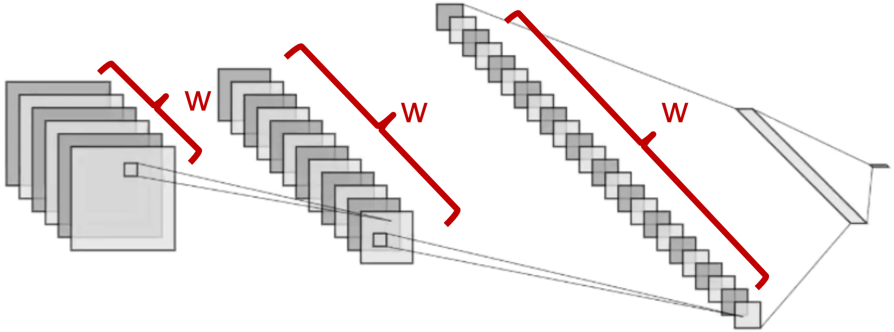


$$\max_{d,w,r}\ Accuracy(Network(d,w,r))$$
$$s.t.\ Hardware\ requiered < Hardware\ capabilities$$
$$d \geq 1, w \geq 1, r \geq 1$$

3. Increase the number of channels **(w=2)**



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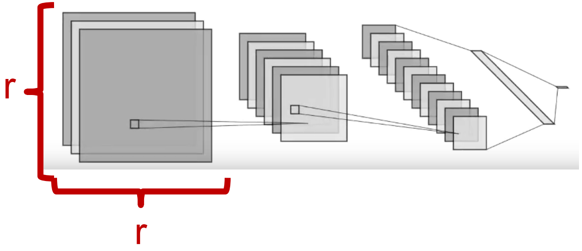

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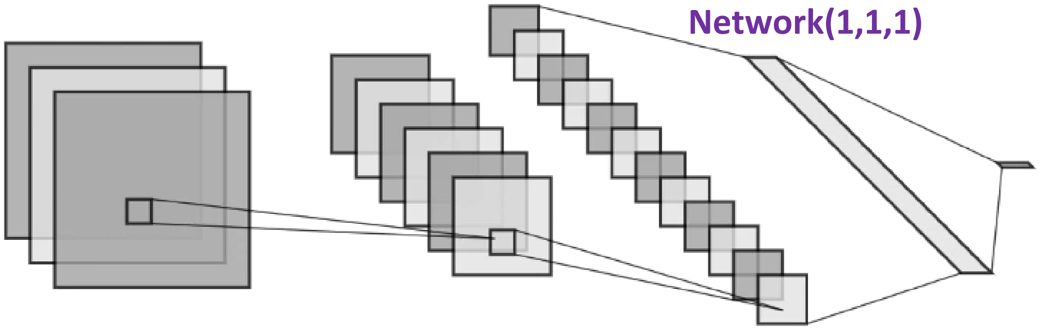

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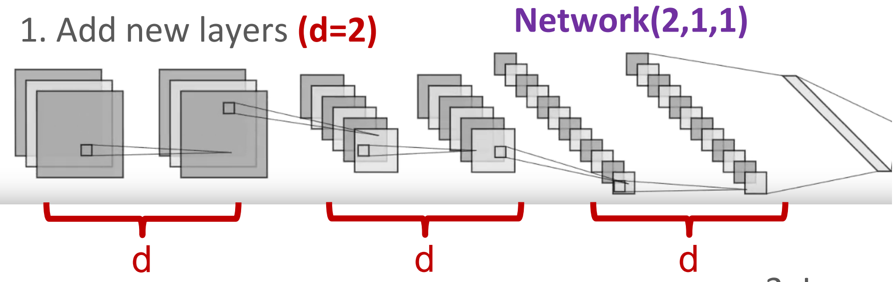
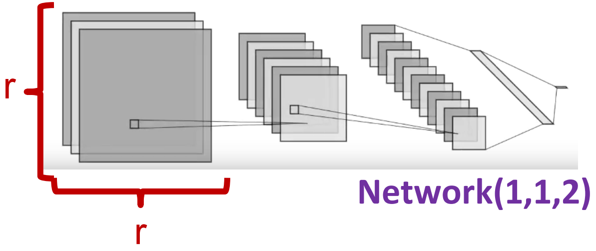


$$\max_{d,w,r} \; Accuracy(Network(d,w,r))$$
$$s.t. \; Hardware\ requiered < Hardware\ capabilities$$
$$d \geq 1, w \geq 1, r \geq 1$$

2. Increase height and width **(r=2)**



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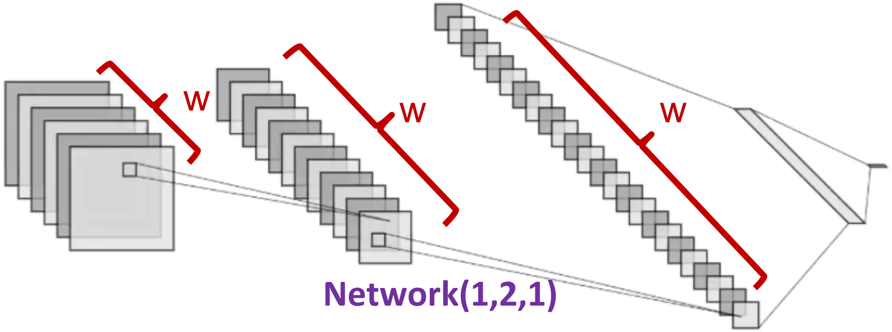

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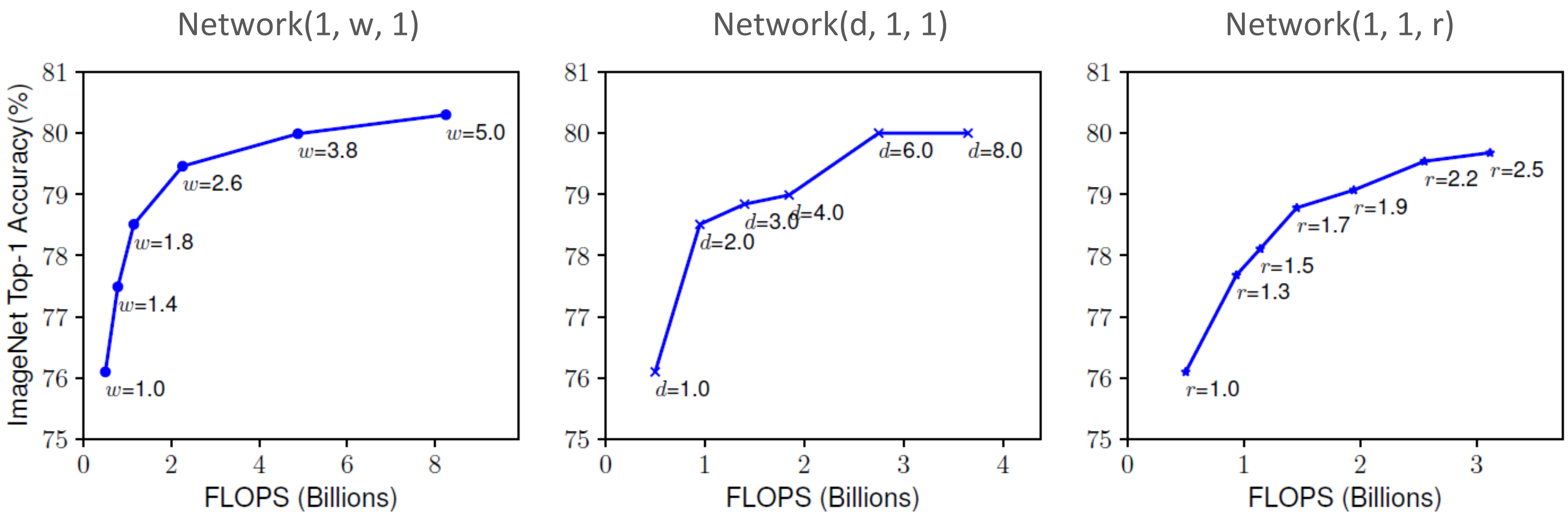


FLOPS: Float Operations Per Second

1. How to scale

Hypothesis: Scale d, r, w evenly. We can define $\alpha,\ \beta,\ \gamma$ s.t.

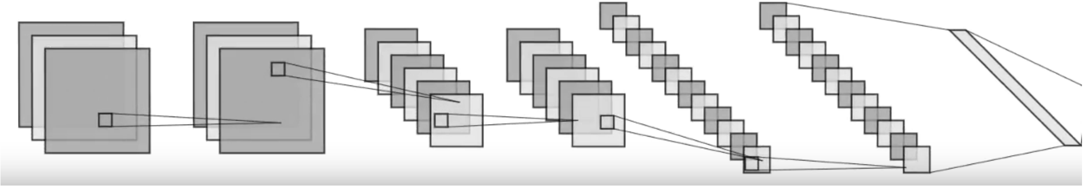
$$d = \alpha^{\phi}$$
$$w = \beta^{\phi}$$
$$r = \gamma^{\phi}$$

$$\max_{d,w,r} \ Accuracy(Network(d,w,r))$$
$$s.t.\ Hardware\ requiered < Hardware\ capabilities$$
$$d \geq 1, \qquad w \geq 1, \qquad r \geq 1$$

$$\max_{d,w,r} \ Accuracy(Network(\alpha,\beta,\gamma))$$
$$s.t.\ Hardware\ requiered < Hardware\ capabilities$$
$$\alpha \geq 1, \qquad \beta \geq 1, \qquad \gamma \geq 1$$

We can find the best parameters $\alpha,\ \beta,\ \gamma$ using grid search

1. How to scale



$$FLOPS\big(Network(d,w,r)\big) \propto d \cdot FLOPS\big(Network(1,1,1)\big)$$

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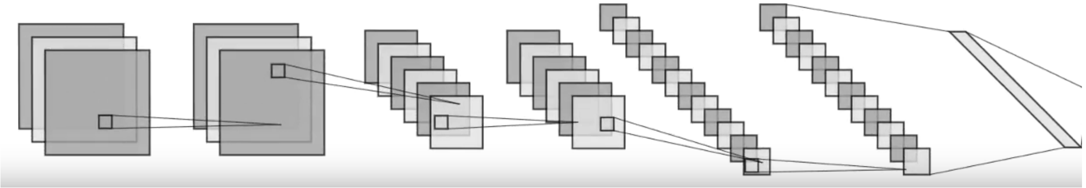
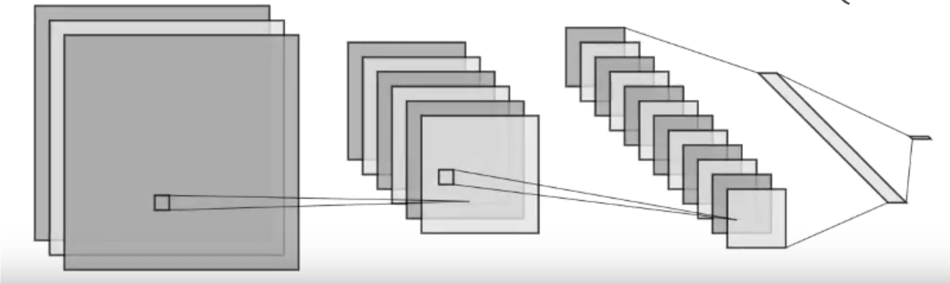
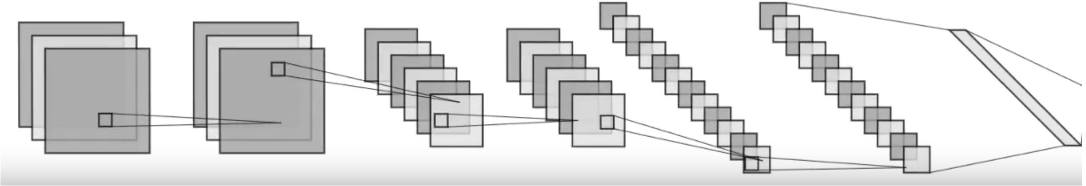


$$FLOPS(Network(d,w,r)) \propto d \cdot FLOPS(Network(1,1,1))$$

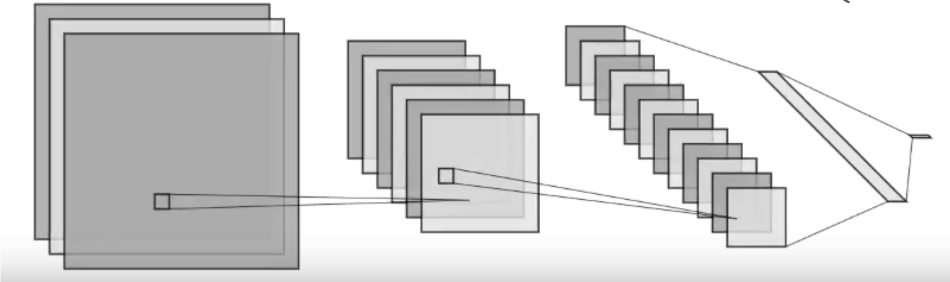


$$FLOPS(Network(d,w,r)) \propto r^2 \cdot FLOPS(Network(1,1,1))$$

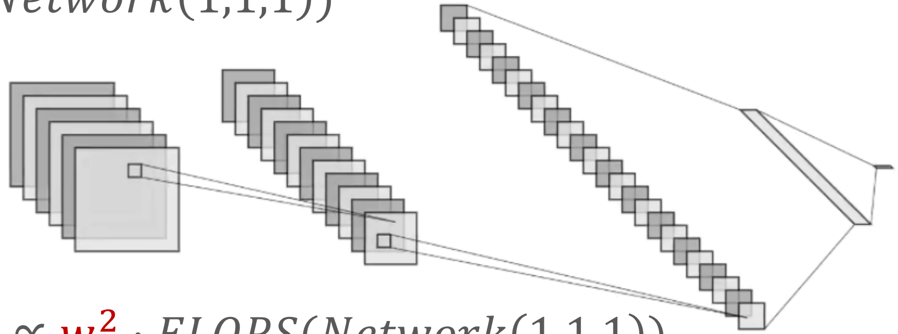
1. How to scale



$$FLOPS\big(Network(d,w,r)\big) \propto d \cdot FLOPS\big(Network(1,1,1)\big)$$



$$FLOPS\big(Network(d,w,r)\big) \propto r^2 \cdot FLOPS(Network(1,1,1))$$



$$FLOPS\big(Network(d,w,r)\big) \propto w^2 \cdot FLOPS(Network(1,1,1))$$

1. How to scale

$$FLOPS\big(Network(d, w, r)\big) \propto dw^2r^2 \cdot FLOPS\big(Network(1,1,1)\big)$$

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$$FLOPS\big(Network(d,w,r)\big) = \alpha\beta^{2\phi}\gamma^{2\phi} \cdot FLOPS\big(Network(1,1,1)\big)$$

$$\frac{FLOPS\big(Network(d,w,r)\big)}{FLOPS\big(Network(1,1,1)\big)} = (\alpha\beta^2\gamma^2)^\phi = 2^\phi$$

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$$\frac{FLOPS\big(Network(d,w,r)\big)}{FLOPS\big(Network(1,1,1)\big)} = (\alpha\beta^2\gamma^2)^\phi = 2^\phi$$

$$\max_{d,w,r} \; Accuracy(Network(\alpha,\beta,\gamma))$$

$$\alpha\beta^2\gamma^2 \approx 2$$

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

Given a network, ϕ is used to define EfficientNet B0 (ϕ=1), …, B7 (ϕ=8)

2. Architecture

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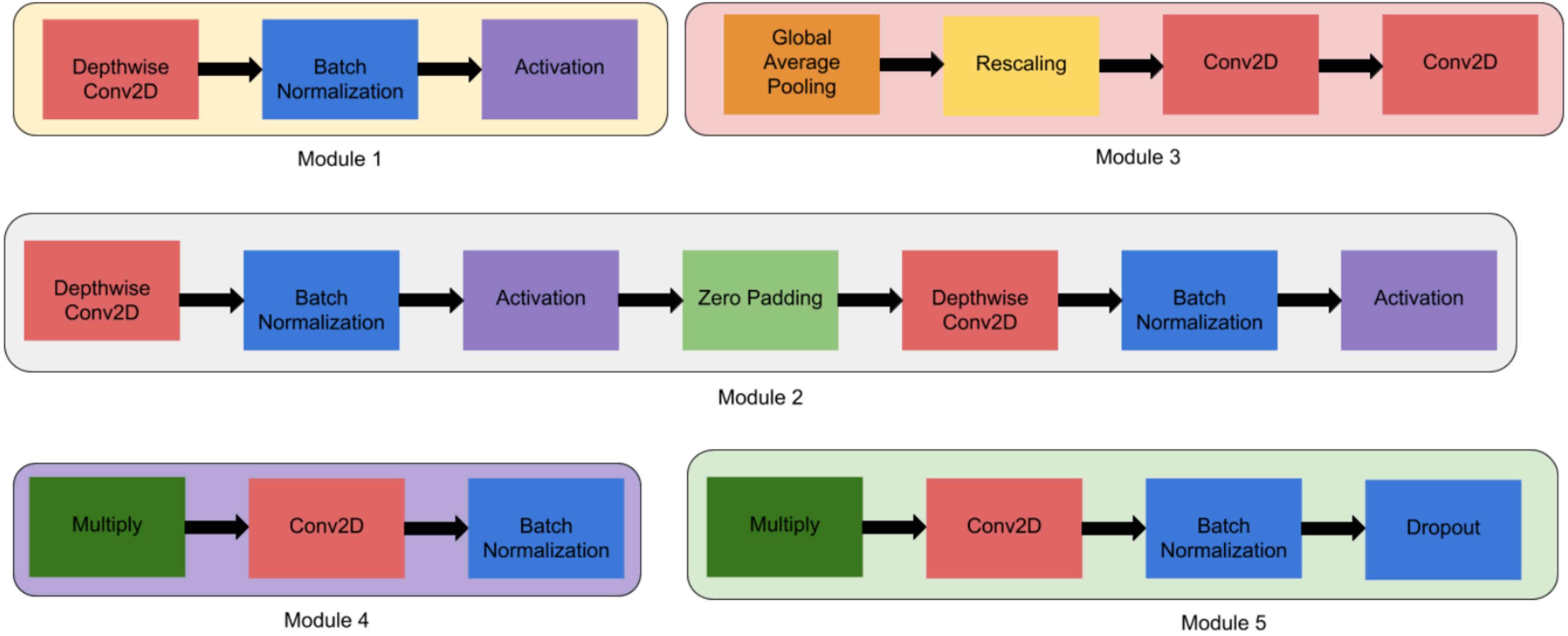

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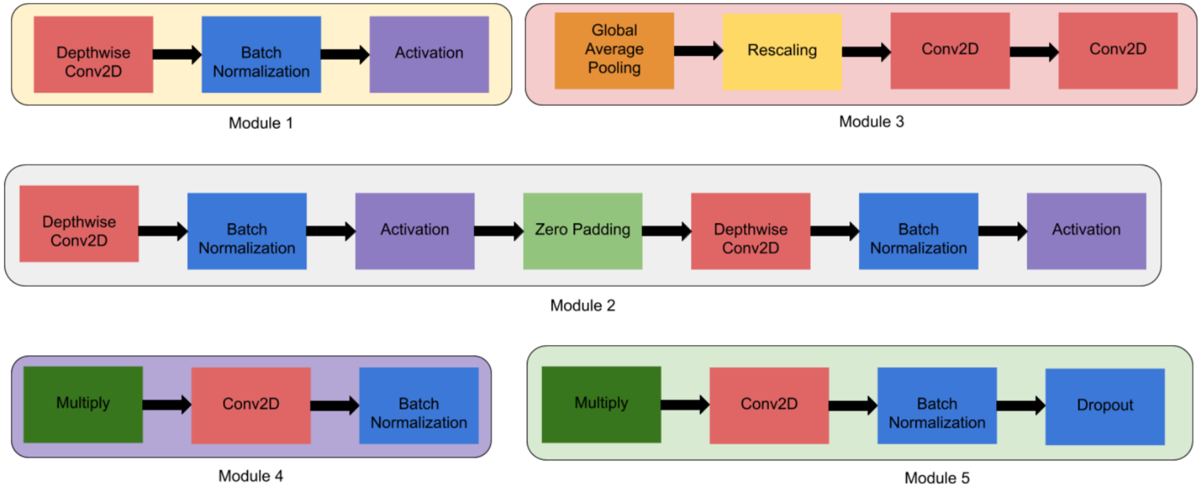

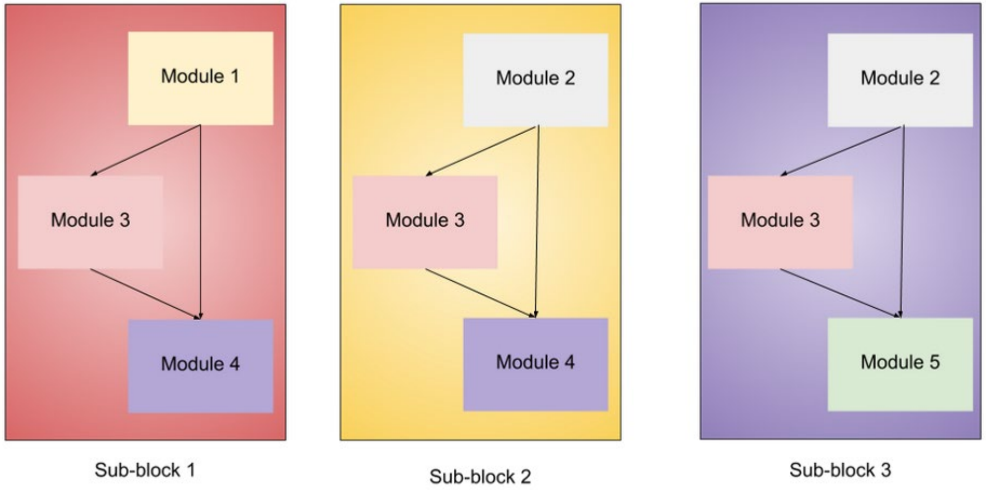

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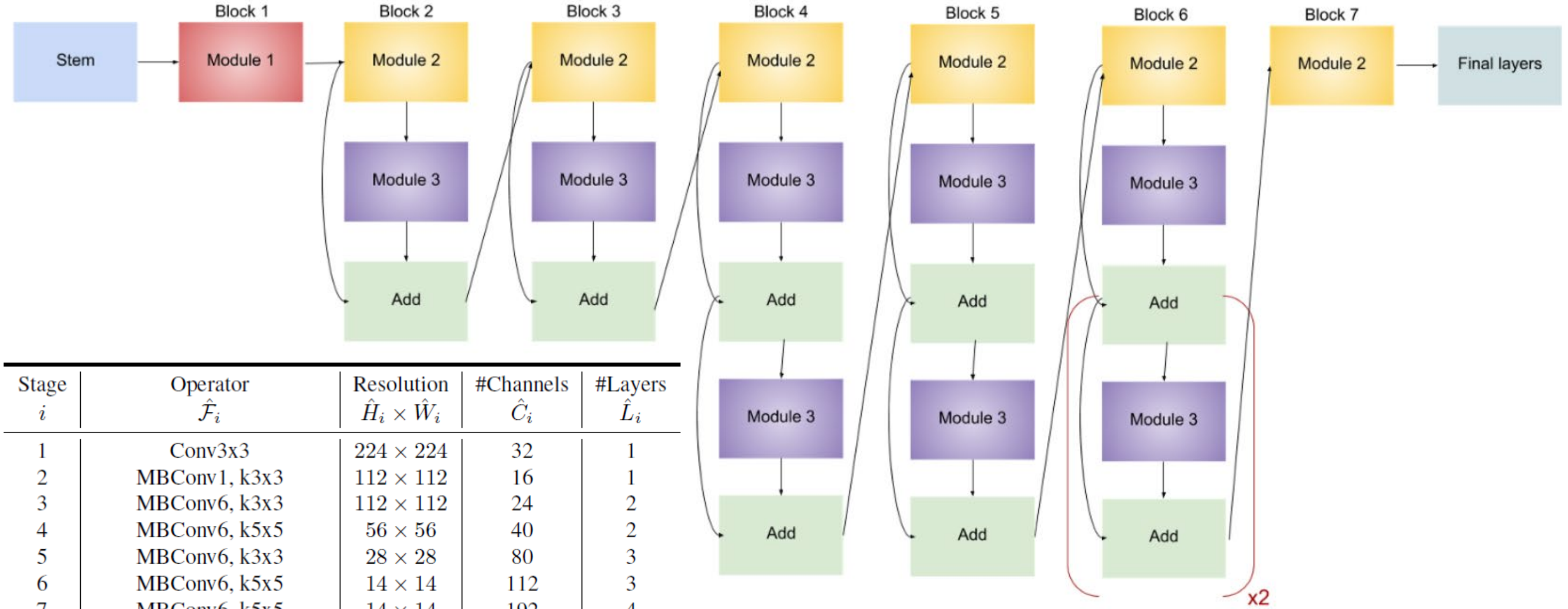


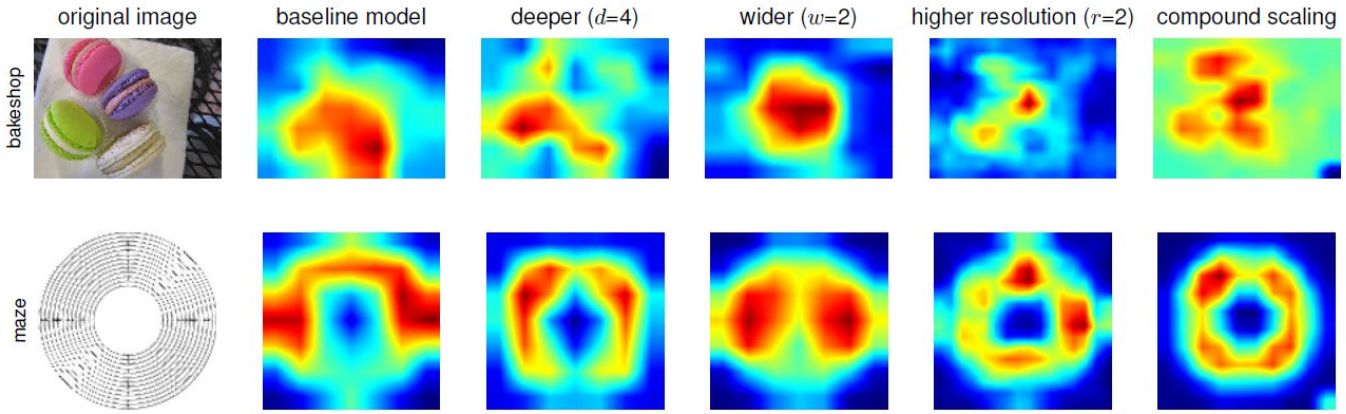
Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14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

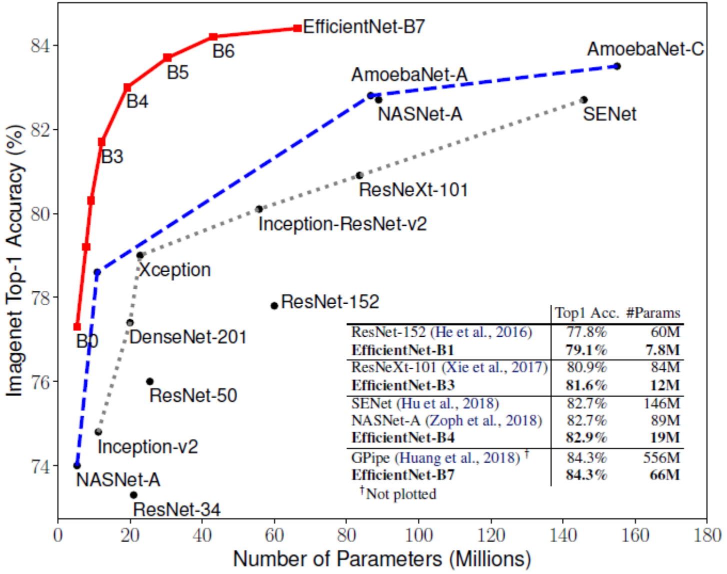
MBConv: mobile inverted bottleneck (https://arxiv.org/abs/1801.04381v4)

3. Results

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNet
EfficientNet-B0	**77.1%**	**93.3%**	**5.3M**	**1x**	**0.39B**	**1x**
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	**79.1%**	**94.4%**	**7.8M**	**1x**	**0.70B**	**1x**
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	**80.1%**	**94.9%**	**9.2M**	**1x**	**1.0B**	**1x**
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	**81.6%**	**95.7%**	**12M**	**1x**	**1.8B**	**1x**
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	**82.9%**	**96.4%**	**19M**	**1x**	**4.2B**	**1x**
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	**83.6%**	**96.7%**	**30M**	**1x**	**9.9B**	**1x**
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	**84.0%**	**96.8%**	**43M**	**1x**	**19B**	**1x**
EfficientNet-B7	**84.3%**	**97.0%**	**66M**	**1x**	**37B**	**1x**
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

3. Results





	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.1%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.6%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.9%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.3%**	**66M**

†Not plotted

Thanks!