

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

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BACKGROUND

EVOLUTION OF CNNs





EfficientNet

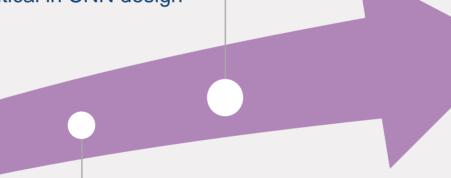
AlexNet (2012)

First winner of the ImageNet challenge based on a CNN



VGGNet (2014)

Depth is critical in CNN design



GoogLeNet (2014)

Reduce parameter count, memory usage, and computation



EVOLUTION OF CNNs



Observation 1:

More sophisticated architecture

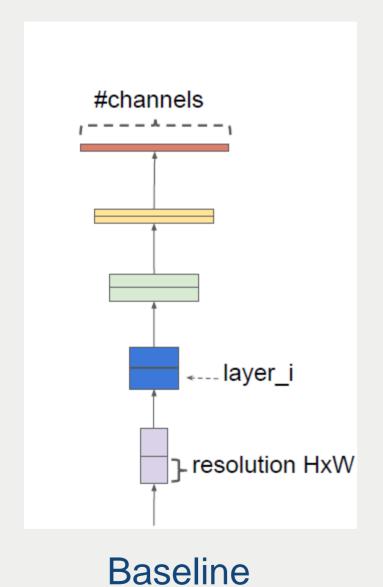
Larger scale

Better performance



MOTIVATION

SCALING UP CNNs



Add more layers



Depth coefficient: d (In this case, d=2)

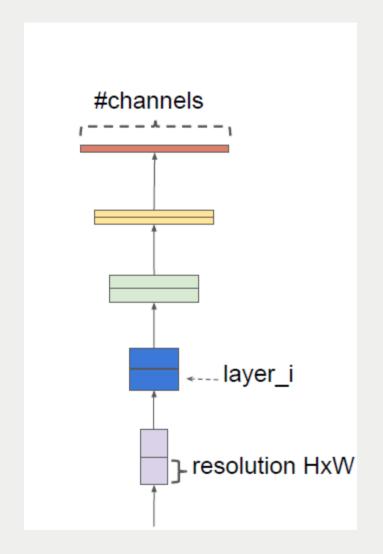
deeper

Depth scaling



SCALING UP CNNs

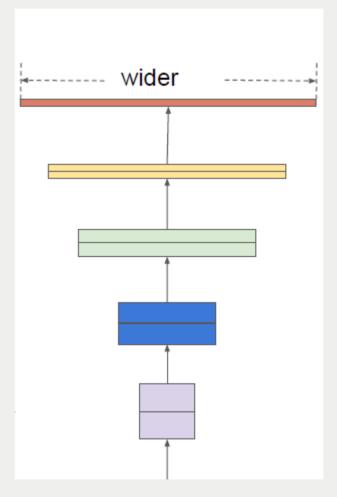








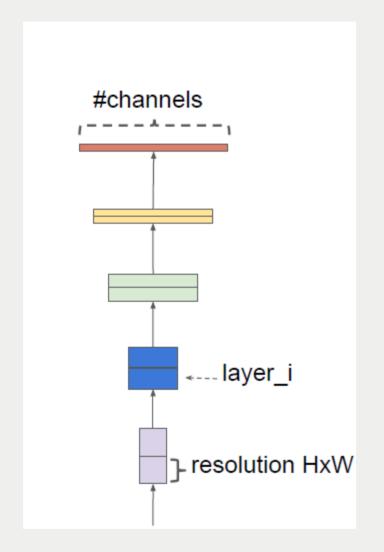
Width coefficient: w



Baseline

Width scaling

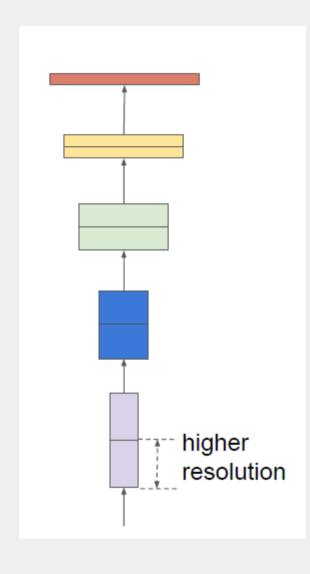
SCALING UP CNNs



Higher resolution of input image



Resolution coefficient: r



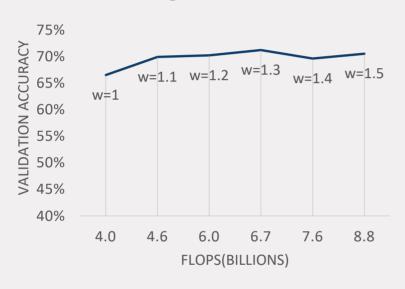


Resolution scaling

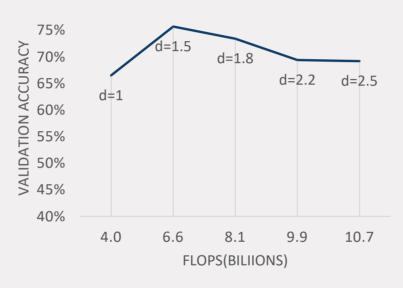
EMPIRICAL STUDY



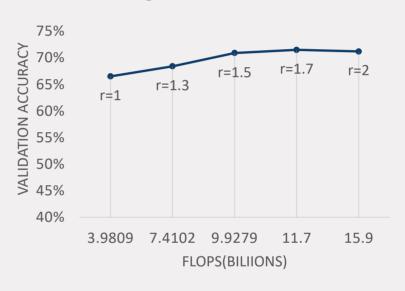
Change in Width



Change in Depth



Change in Resolution



Experiment setting:

- Baseline: EfficientNet-B0 (Structure will be detailed discussed later)
- Dataset: CIFAR-10 with only 3 classes (cat, deer and dog),
 15k~ training samples, 3k~ testing samples
- Epochs: 40

EMPIRICAL STUDY



Observation 2:

Scaling up any dimension of network width, depth, or resolution improves accuracy, but the degree of benefit diminishes as the models grow larger.



MOTIVATION



But different scaling dimensions are not independent.

They are interrelated.

MOTIVATION



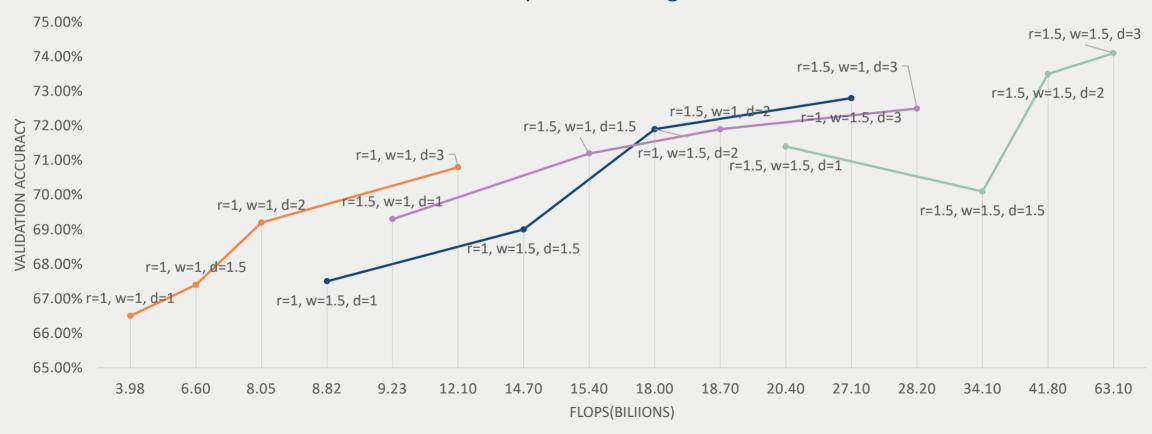
So.....

Uniformly scaling up the coefficients!

Compound Scaling



Compound Scaling



Compound Scaling



Observation 3:

In order to pursue better accuracy and efficiency, it is critical to balance all dimensions of network width, depth, and resolution during ConvNet scaling.

MOTIVATION



Based on observation 2 & 3 ——

Observation 2:

Scaling up any dimension of network improves accuracy, but the degree of benefit diminishes as the models grow larger.

Observation 3:

We need to balance all dimensions of network during ConvNet scaling.

MOTIVATION



Based on observation 2 & 3 ——

Question:

How to balance the three dimensions of neural networks?

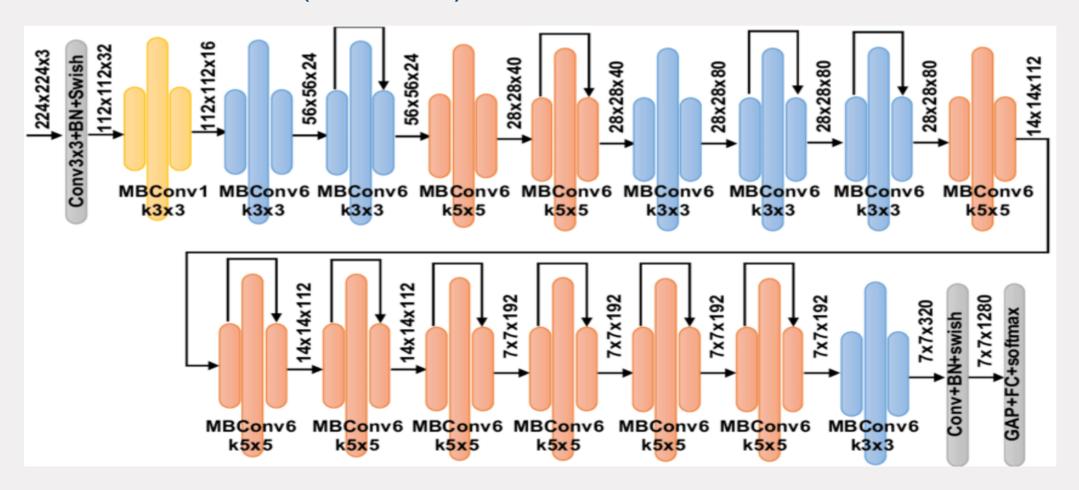


REPRODUCTION

EFFICIEFFICIENTNET BO ARCHITECTURE

Before talking about result, go through the general architecture of EfficientNet B0 (Baseline).





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MARR

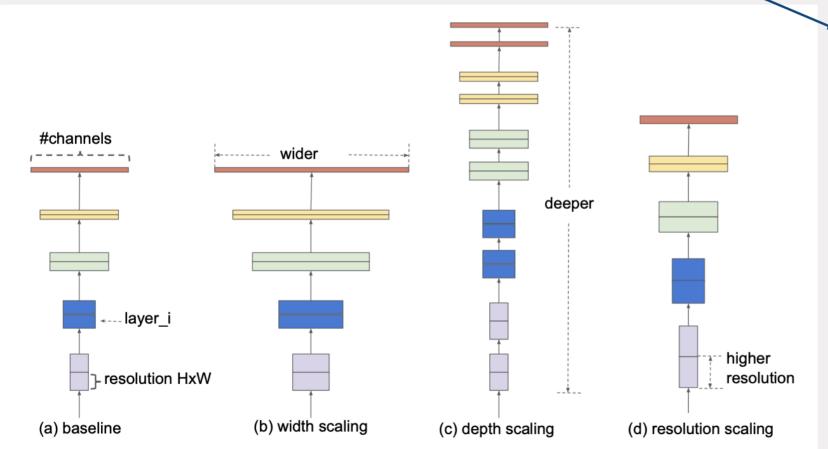
To conclude, there are two main parts for our reproduction:

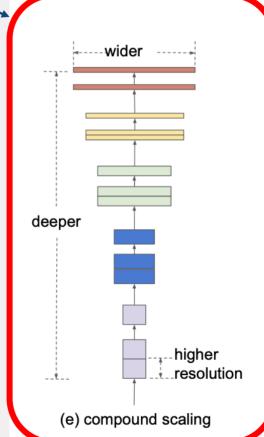
1. To determine the optimal combination of depth, width, and resolution for specific computation resources.

2. Compare the performance of EfficientNet with other convolutional neural network (CNN) architectures.

First part: Determine combination of depth, width, resolution

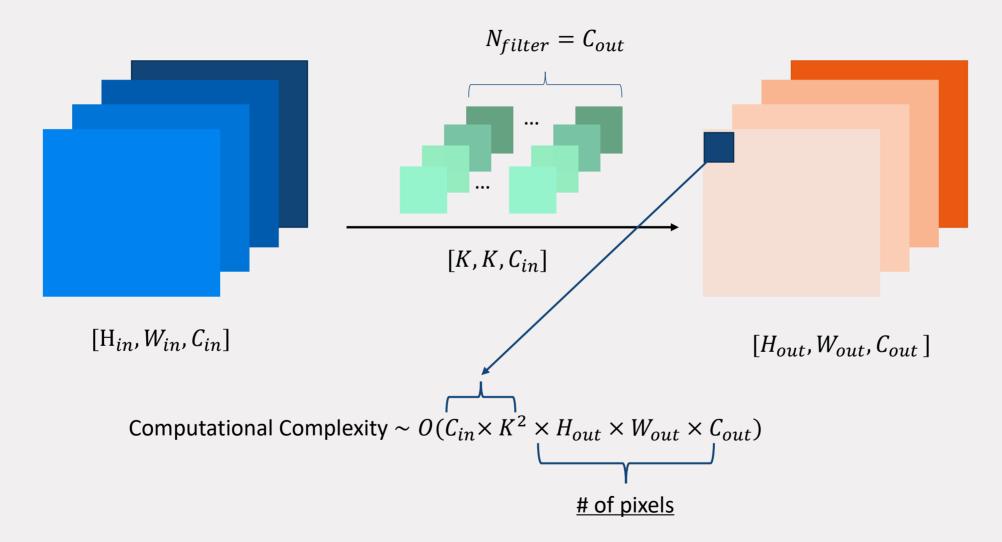
Efficient Net proposes 'Compound Scaling' Scheme to determine the optimal scaling factors.







First part: Determine combination of depth, width, resolution





First part: Determine combination of depth, width, resolution



Result: Computational Complexity $\sim O(C_{in} \times K^2 \times H_{out} \times W_{out} \times C_{out})$

Scaling factor: $\beta \leftarrow Width$: $w \leftarrow C_{in}, C_{out}$)

Scaling factor: γ \leftarrow Resolution: r \leftarrow (H_{out}, W_{out})

Conclusion1: if we enlarge width by β and resolution by γ , then the computational costs will be proportional to $(\beta^2 \cdot \gamma^2)$ times.

Scaling factor: α \longleftarrow Depth: d \longleftarrow (# of convolution modules)

Conclusion2: if we enlarge depth by α , then the computational costs will be proportional to α times.

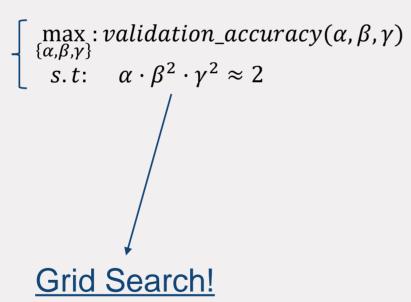
Conclusion3: if we enlarge 3 factors by (α, β, γ) respectively, then the computational costs will be **proportional to** $(\alpha \cdot \beta^2 \cdot \gamma^2)$ **times.**

First part: Determine combination of depth, width, resolution

'Compound Scaling' Scheme:

Question: if now, our resources are N times larger, how to allocate for these 3 scaling factors?

• Step 1: Assume twice more resources are available, as we illustrate in the previous slide, we are required to solve:





First part: Determine combination of depth, width, resolution

Grid Search Result:



index	α	β	γ	best_train_accuracy	best_val_accuracy
<u>1</u>	<u>1.2</u>	<u>1.1</u>	<u>1.15</u>	<u>86.02%</u>	<u>93.17%</u>
2	1.2	1.15	1.1	84.85%	92.40%
3	1.3	1.05	1.15	85.10%	92.12%
4	1.3	1.15	1.05	84.21%	92.03%
5	1.15	1.1	1.2	85.07%	92.26%
6	1.1	1.2	1.15	84.71%	92.52%

 $\underline{s.t \ \alpha \times \beta^2 \times \gamma^2 \approx 2}$

Experiment setting:

• Baseline: EfficientNet-B0

Dataset: CIFAR-10 with 10 classes

• Epochs: 100



First part: Determine combination of depth, width, resolution

'Compound Scaling' Scheme:

Question: if now, our resources are N times larger, how to allocate for these 3 scaling factors?

• Step 1: Assume twice more resources are available, as we illustrate in the previous slide, we are required to solve:

$$\begin{cases} \max_{\{\alpha,\beta,\gamma\}} : validation_accuracy(\alpha,\beta,\gamma) \\ s.t: \quad \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \end{cases}$$

• Step 2: Now we achieve the optimal $(\hat{\alpha}, \hat{\beta}, \hat{\gamma})$ and in the question, we have \underline{N} times more computation resources. In this setting, the optimal scaling factors $(\alpha^*, \beta^*, \gamma^*)$ can be determined as follows:

$$\begin{cases}
\alpha^*, \beta^*, \gamma^* = \hat{\alpha}^{\phi}, \hat{\beta}^{\phi}, \hat{\gamma}^{\phi} \\
\phi = \log_2 N
\end{cases}$$

$$\begin{cases}
d^* = d_0 \cdot \alpha^* \\
w^* = w_0 \cdot \beta^* \\
r^* = r_0 \cdot \gamma^*
\end{cases}$$



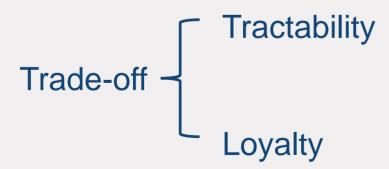
First part: Determine combination of depth, width, resolution



Big, Intractable Grid Search Problem (N times more resources)

Uniform Scaling Parameter ϕ

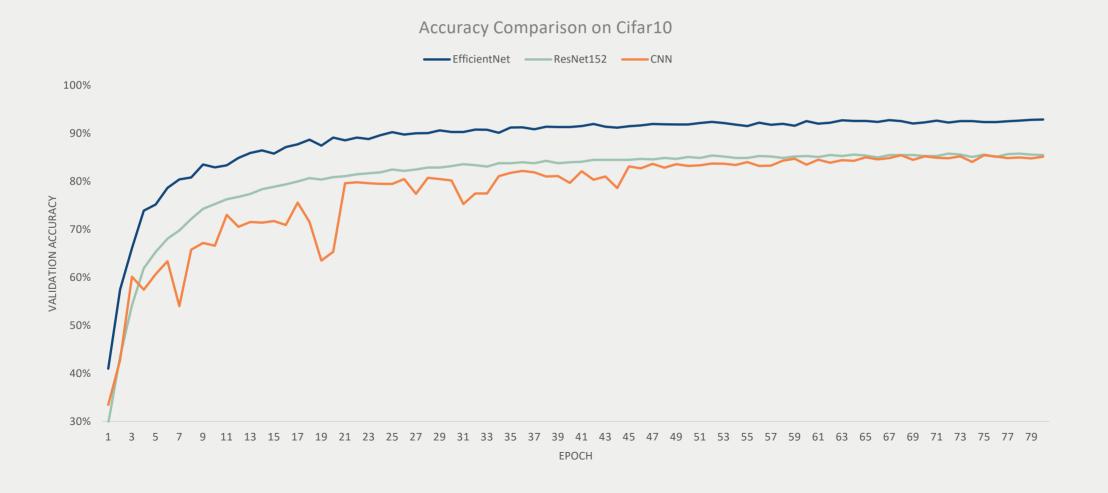
Small, Tractable Grid Search Problem (2 times more resources)



Second Part: Comparison between EfficientNet and other Network Architectures

Compare between EfficientNet and other CNN architectures including the CNN given in our lecture and famous ResNet152 on CIFAR10 Dataset.







EXTENSION

EXTENSION



Two possible directions of extension:

1 Apply EfficientNet on CIFAR100 dataset

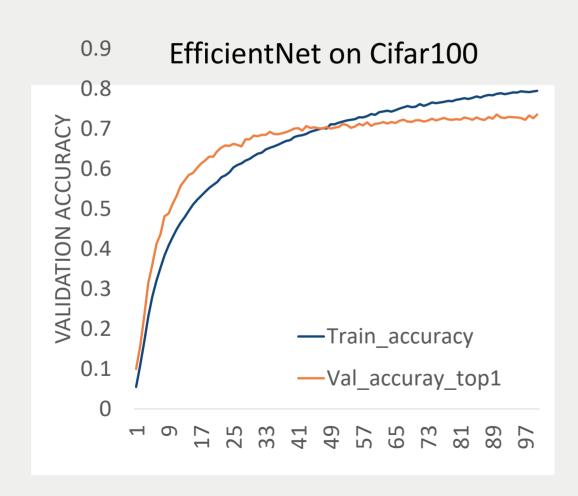
2 Improve the EfficientNet Architecture

EFFICIENTNET EXTENSION

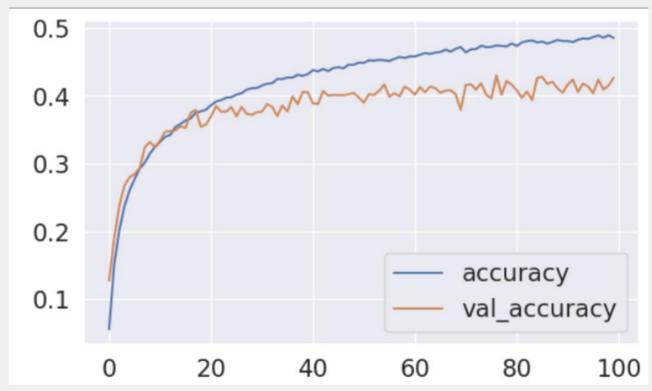
First part: Apply EfficientNet on CIFAR100 Dataset

Compare between EfficientNet and the CNN given in our lecture on CIFAR100 Dataset.





CNN on Cifar100



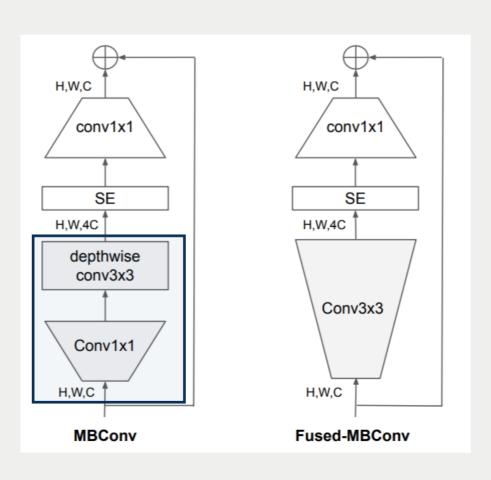
EFFICIENTNET EXTENSION

Second part: Improve EfficientNet Architecture

Limitations of the EfficientNet architecture,

- 1. Training with very large image sizes is slow
- 2. Depthwise convolutions are slow in early layers

To overcome these limitations, we try to replace the depthwise 3x3 convolution and expansion 1x1 convolution in MBConv in EfficientNet with a regular 3x3 convolution.



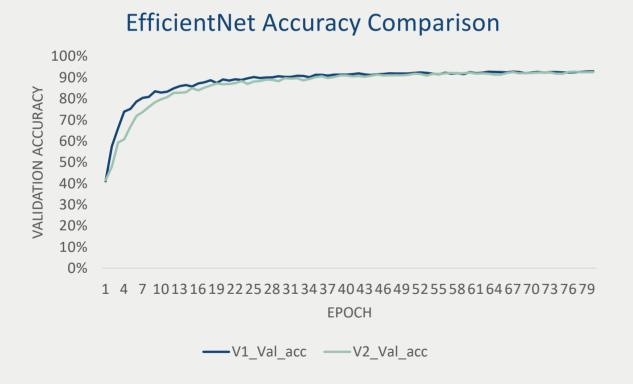


EFFICIENTNET EXTENSION

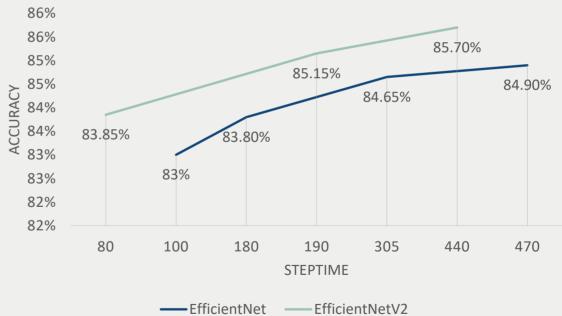
Second part: Improve EfficientNet Architecture



Compare between EfficientNet and EfficientNet V2 with respect to model performance (accuracy) and model efficiency (steptime).



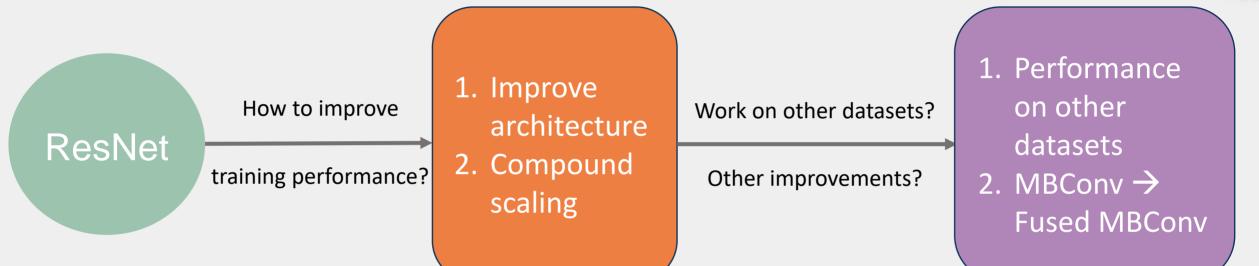
EfficientNet V.S. EfficientNet V2





SUMMARY





SUMMARY

Dataset: CIFAR-10 & CIFAR-100

Platform: Colab with GPU

Library: PyTorch

Links: https://github.com/SizheYang512/DSA5204-2023-Group20

Reference (paper and code):

- 1. ResNet, https://arxiv.org/abs/1512.03385
- 2. EfficientNet, https://arxiv.org/abs/1905.11946
- 3. EfficientNet V2, https://arxiv.org/abs/2104.00298
- 4. Code: https://github.com/qubvel/efficientnet
- 5. Code: https://github.com/WZMIAOMIAO/deep-learning-for-image-processing/tree/master/pytorch_classification/Test9_efficientNet





THANKS

HAVE A NICE DAY!