EfficientNet

Rethinking Model Scaling for Convolutional Neural Networks

3 Min ver.

인공지능 논문 리딩/리뷰 스터디

Abstract

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Convolutional Neural Networks (ConvNets) are commonly developed at a fixed resource budget, and then scaled up for better accuracy if more resources are available. In this paper, we systematically study model scaling and identify that carefully balancing network depth, width, and resolution can lead to better performance. Based on this observation, we propose a new scaling method that uniformly scales all dimensions of depth/width/resolution using a simple yet highly effective *compound coefficient*. We demonstrate the effectiveness of this method on scaling up MobileNets and ResNet.

To go even further, we use neural architecture search to design a new baseline network and scale it up to obtain a family of models, called *EfficientNets*, which achieve much better accuracy and efficiency than previous ConvNets. In particular, our EfficientNet-B7 achieves state-of-the-art 84.3% top-1 accuracy on ImageNet, while being **8.4x smaller** and **6.1x faster** on inference than the best existing ConvNet. Our EfficientNets also transfer well and achieve state-of-the-art accuracy on CIFAR-100 (91.7%), Flowers (98.8%), and 3 other transfer learning datasets, with an order of magnitude fewer parameters. Source code is at https://github.com/tensorflow/tpu/tree/master/models/official/efficientnet.

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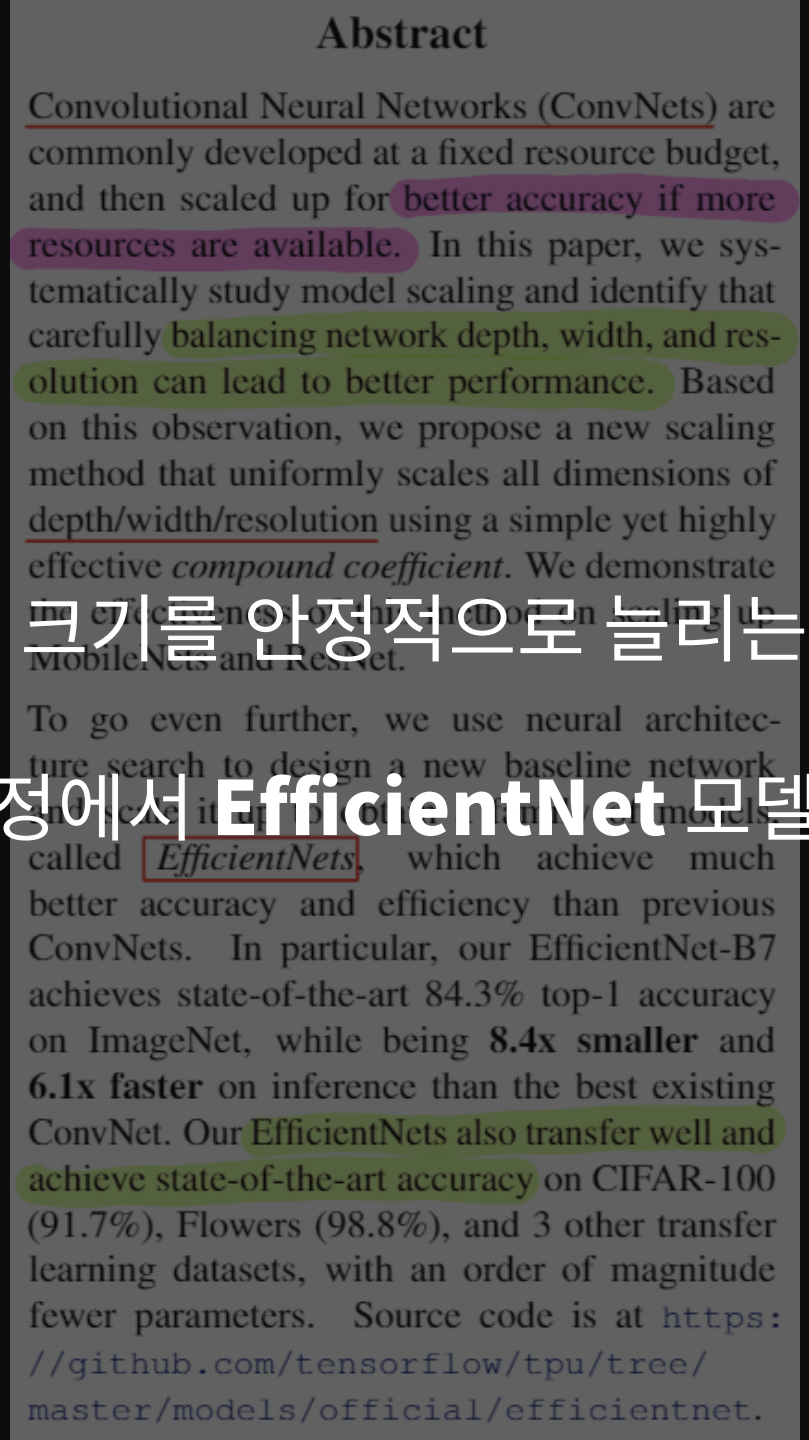
CNN 모델의 크기를 안정적으로 늘리는 방법 연구함

Abstract



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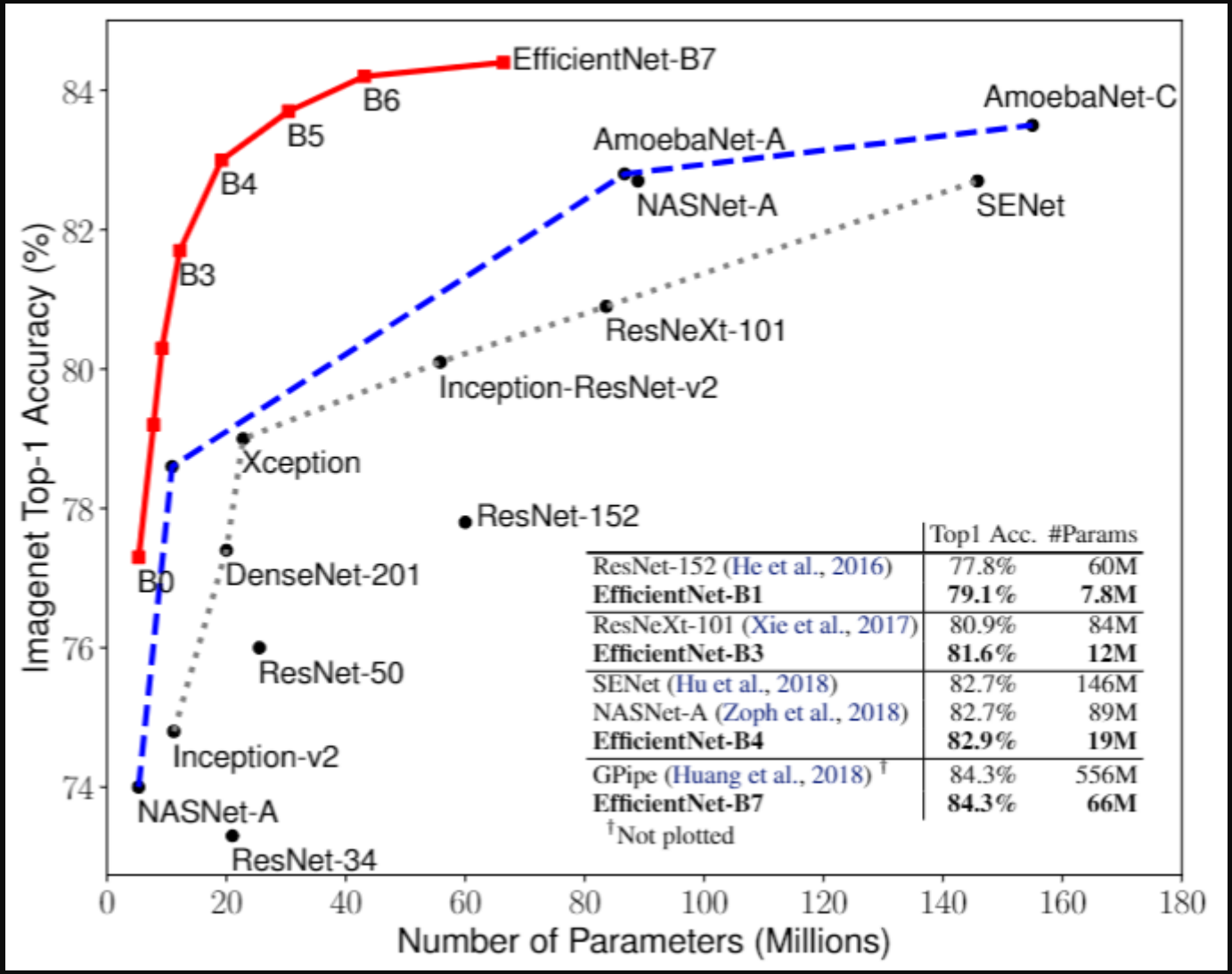
그 과정에서 **EfficientNet** 모델 개발

Introduction



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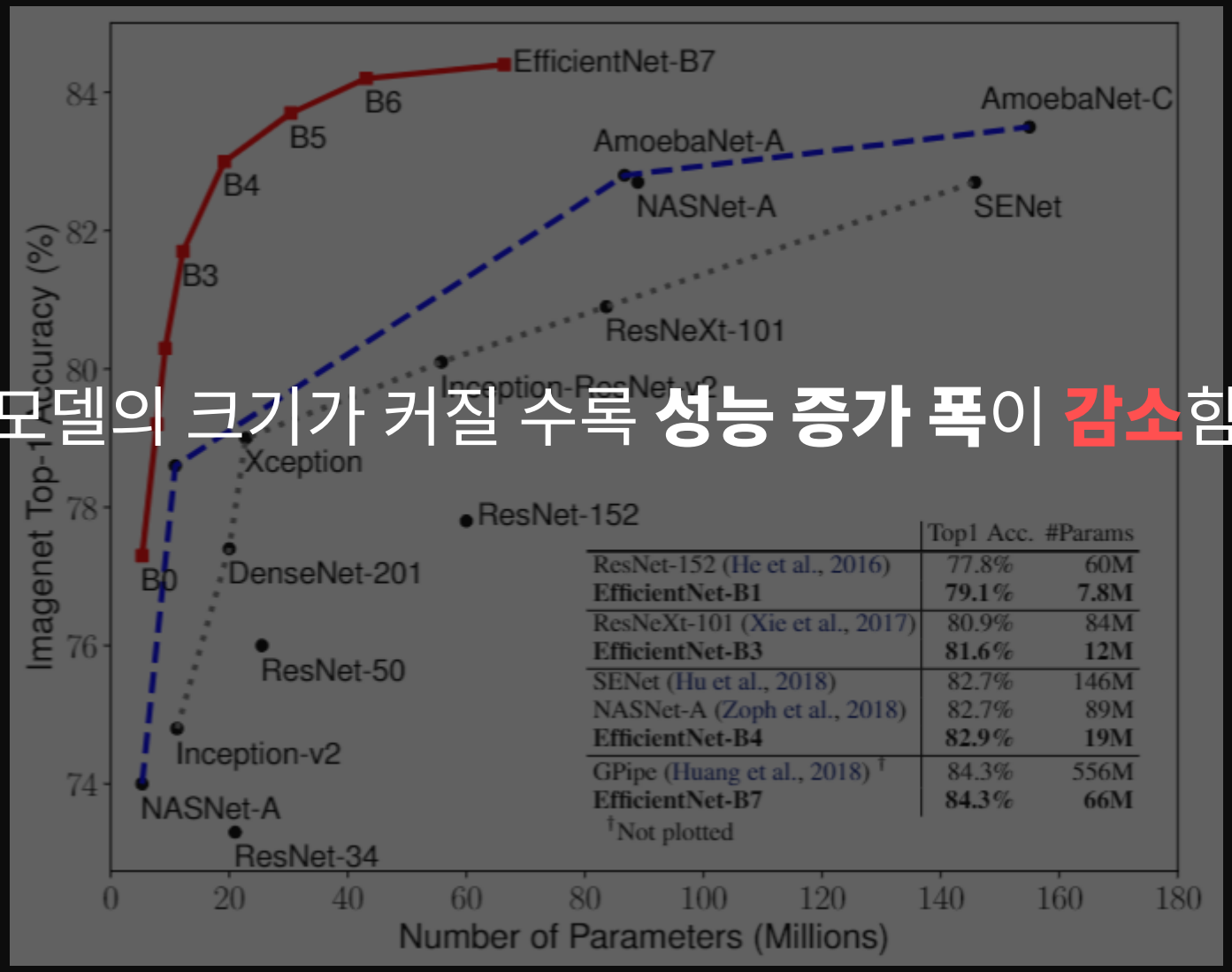

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모델의 크기가 커질 수록 **성능 증가 폭**이 **감소**함

Introduction

Width/Depth/Resolution

위 세가지 수치를 균형 있게 키우자

Introduction

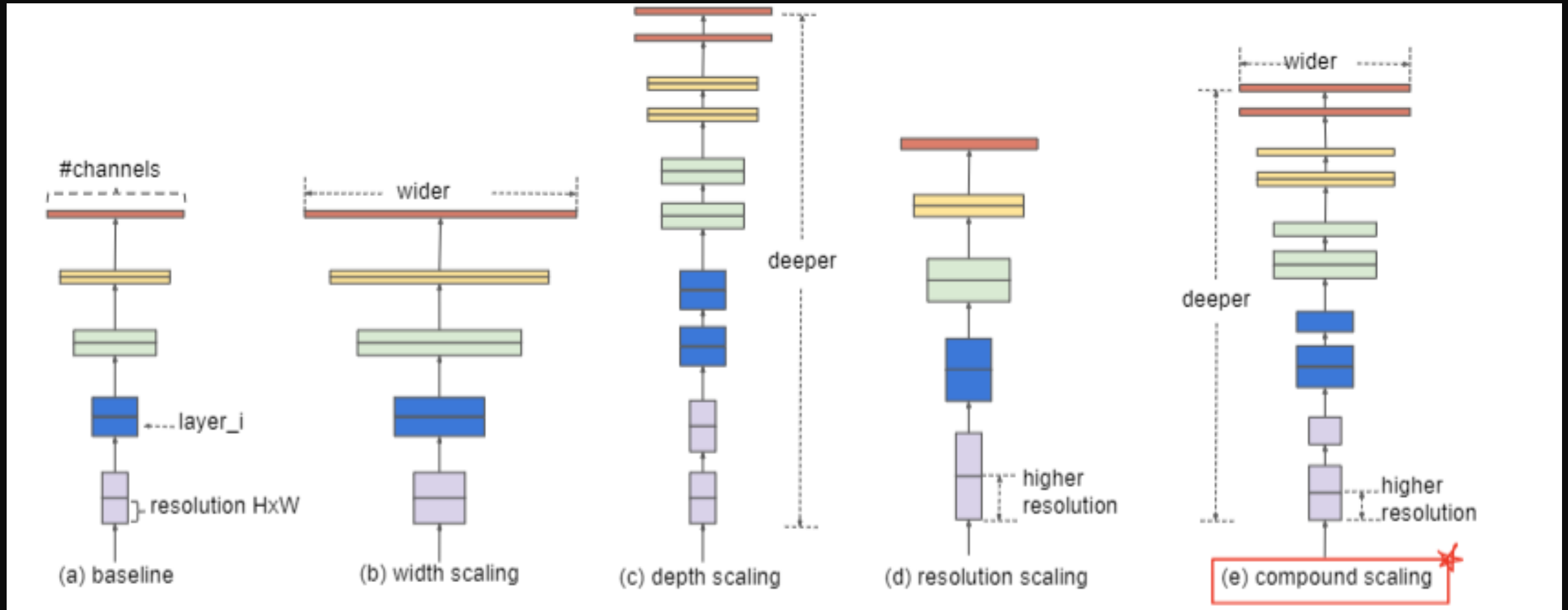

Figure 2. **Model Scaling.** (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

Compound Model Scaling

$$\max_{d,w,r} Accuracy(N(d,w,r))$$

$$s.t. \quad N(d,w,r) = \bigodot_{i=1\ldots s} \hat{F}_i^{d\cdot\hat{L}i}(X_{<r\cdot\hat{H}_i, r\cdot\hat{W}_i, w\cdot\hat{C}_i>})$$

$$Memory(N) \leq target\_memory$$

$$FLOPS(N) \leq target\_flops$$

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

1. grid search

Compound Model Scaling

$$\text{depth: } d = \alpha^\phi \quad (1.2)$$
$$\text{width: } w = \beta^\phi \quad (1.1)$$
$$\text{resolution: } r = \gamma^\phi \quad (1.5)$$
$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$
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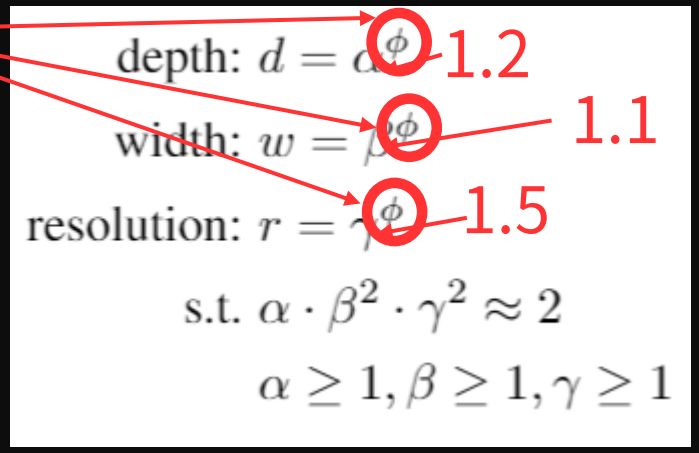
1. grid search

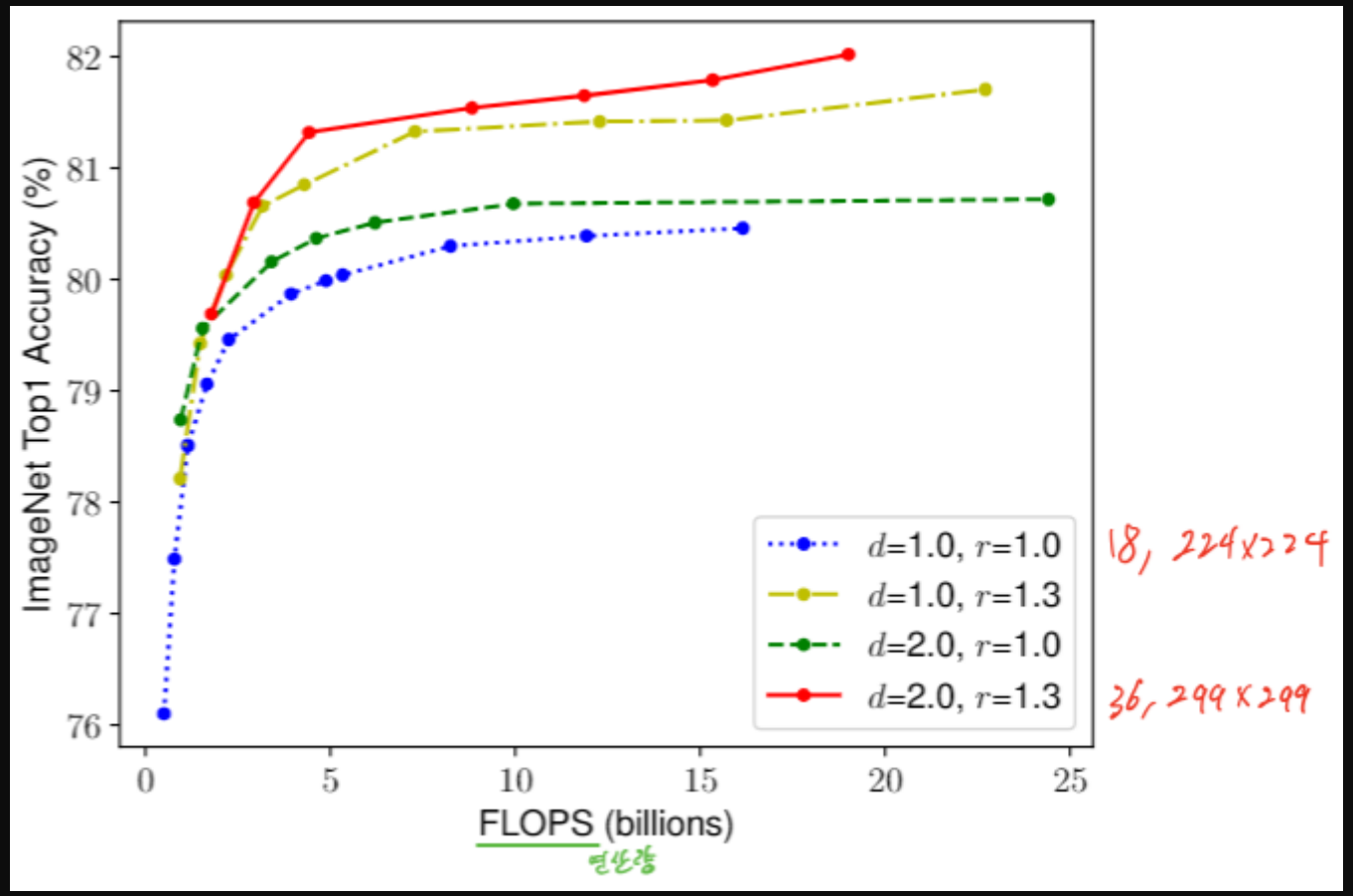
Compound Model Scaling

Phi 값을 증가시켜
Scaling

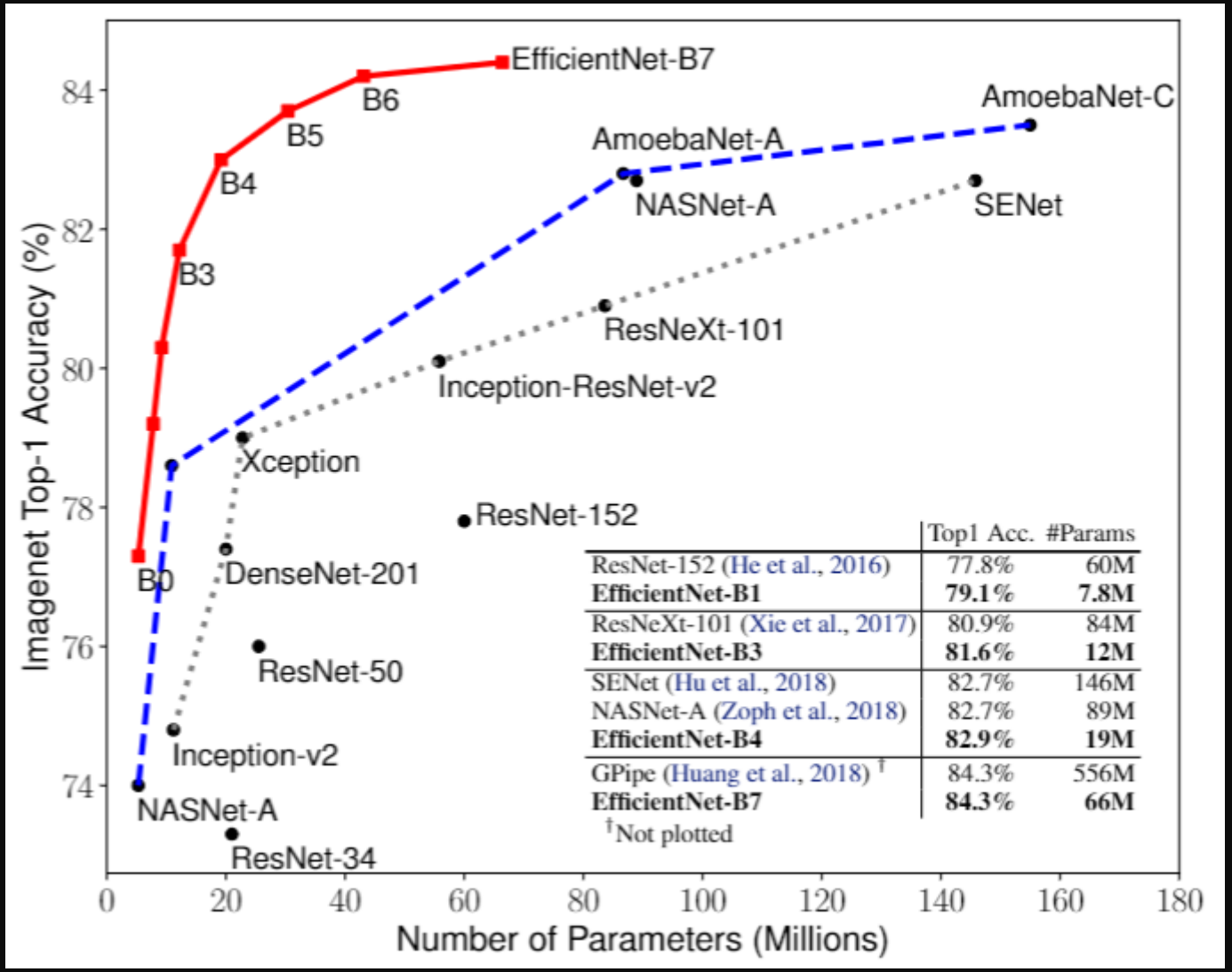


2. Scaling

Compound Model Scaling



결론



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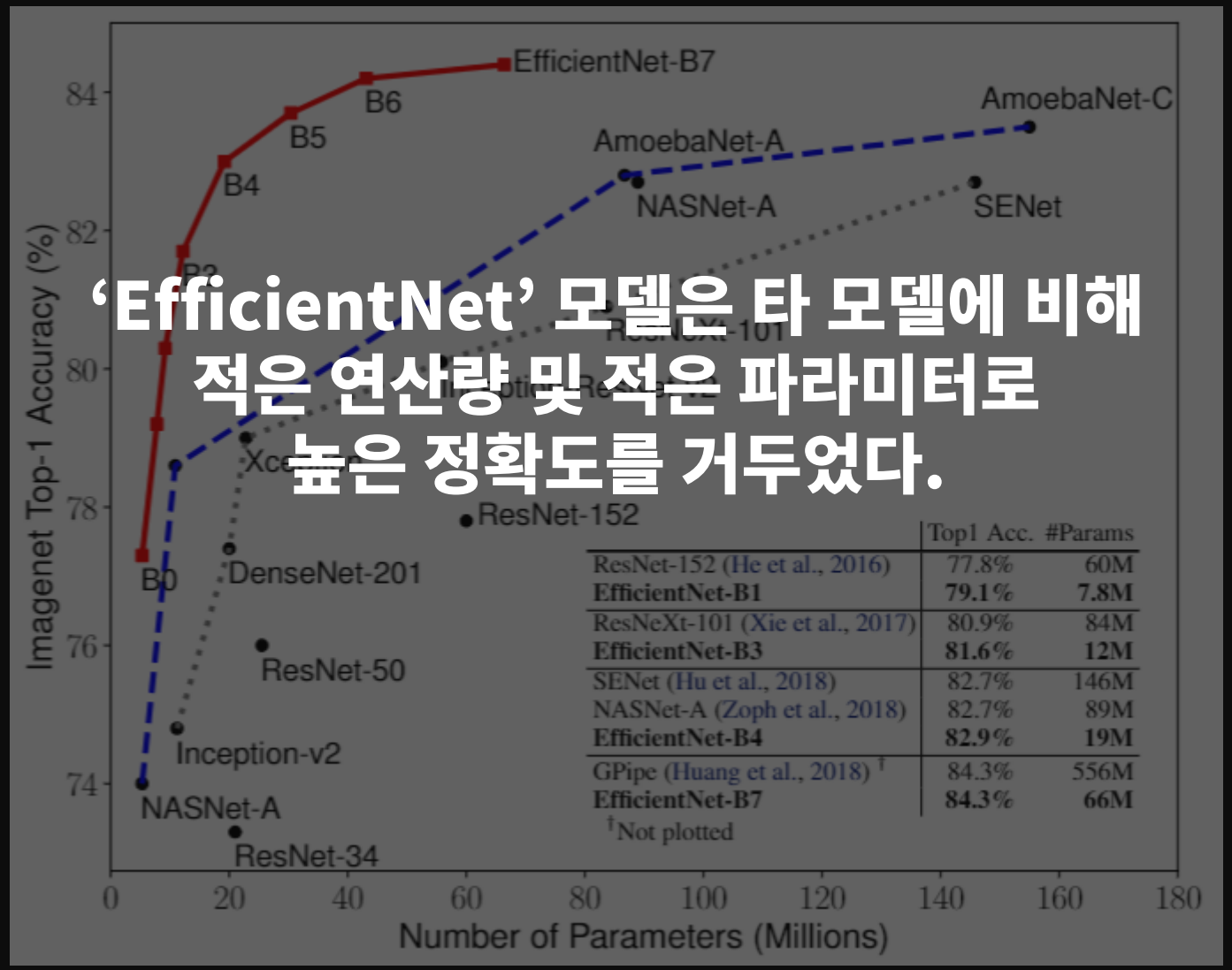

‘EfficientNet’ 모델은 타 모델에 비해 적은 연산량 및 적은 파라미터로 높은 정확도를 거두었다.

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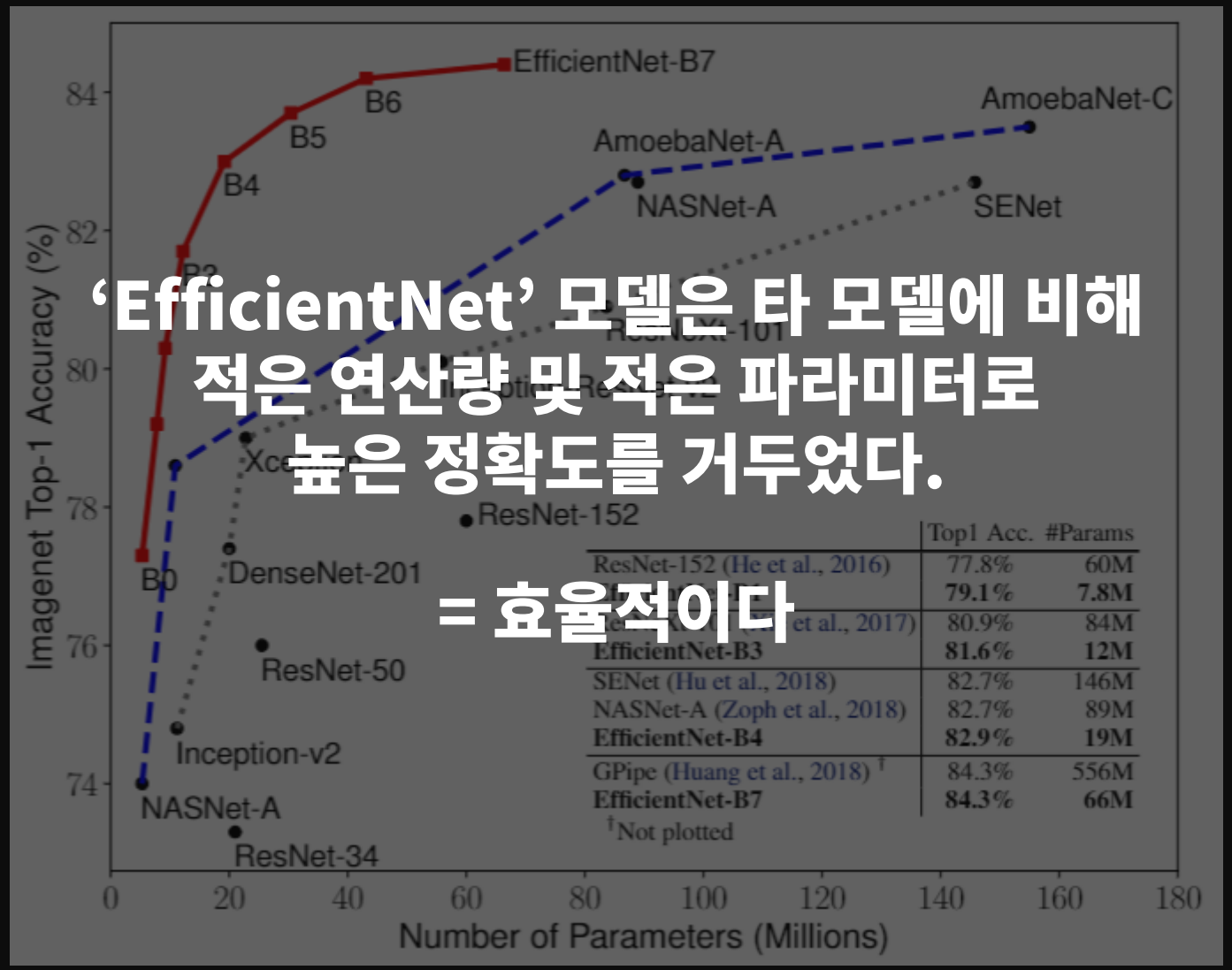

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= 효율적이다

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