# CVPR 2017
# Aggregated Residual Transformations for Deep Neural Networks

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논문 리뷰

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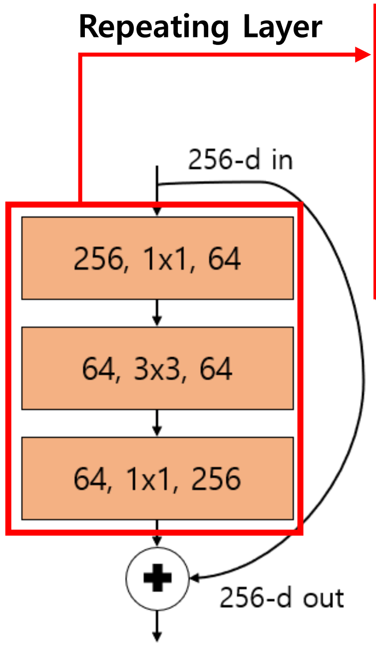
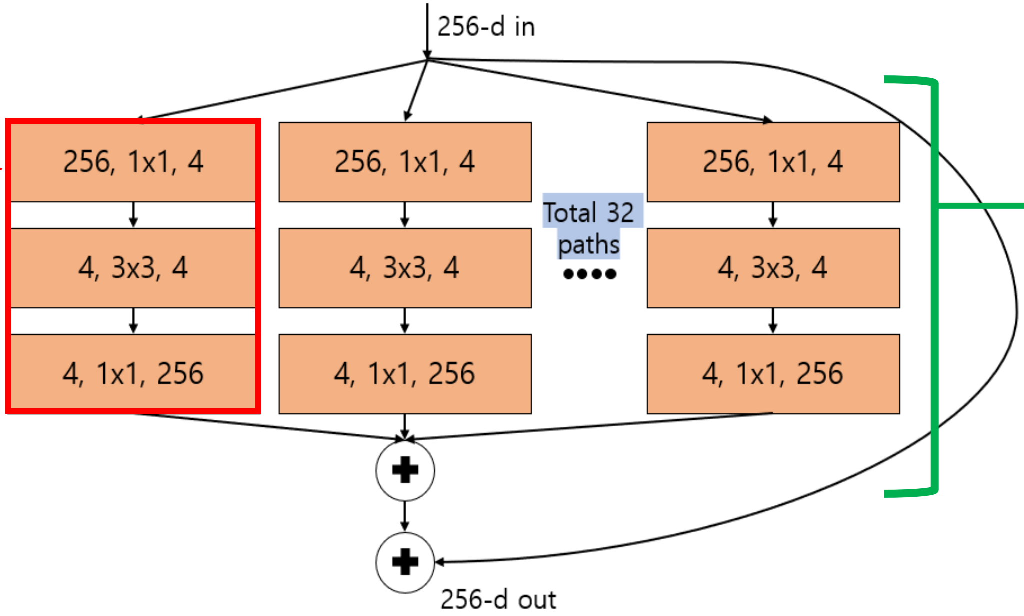
# Aggregated Residual Transformations for Deep Neural Networks (CVPR 2017)

- **Research Background:**
  - 문제: Network Depth가 깊어질수록 **Hyper-parameters 증가**하는 어려움 발생
  - 해결: **Cardinality** 라는 새로운 차원의 도입과 **Hyper-parameter 효율적 조절**을 통해 성능 향상 (ResNet에서 발전)

**Repeating layer 전략**(VGG, ResNet) + "**Cardinarity**" + **Split/Transform/Merge 전략**(InceptionNet) + **Grouped convolution**



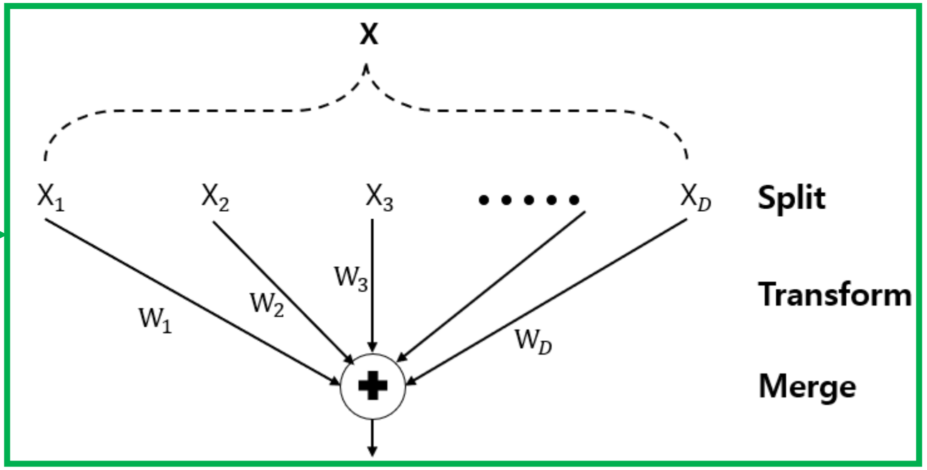

ResNet




**ResNeXt** (C=32, d=4)

C: **Cardinality**, ConvNet을 몇 개로 나눌지

d: ConvNet의 Channel




**Split**: x를 split $(x_1, x_2, x_3, \ldots, x_D)$

**Transform**: weigh을 곱함 $(x_1W_1, x_2W_2, \ldots, x_DW_D)$

**Merge**: 전체 결과 합 $(x_1W_1 + x_2W_2 + \cdots + x_DW_D)$

$$F(x) = \boxed{\sum_{i=1}^{C} T_i(x)} + x_{identity} \longrightarrow y = x + \boxed{\sum_{i=1}^{C} T_i(x)}$$

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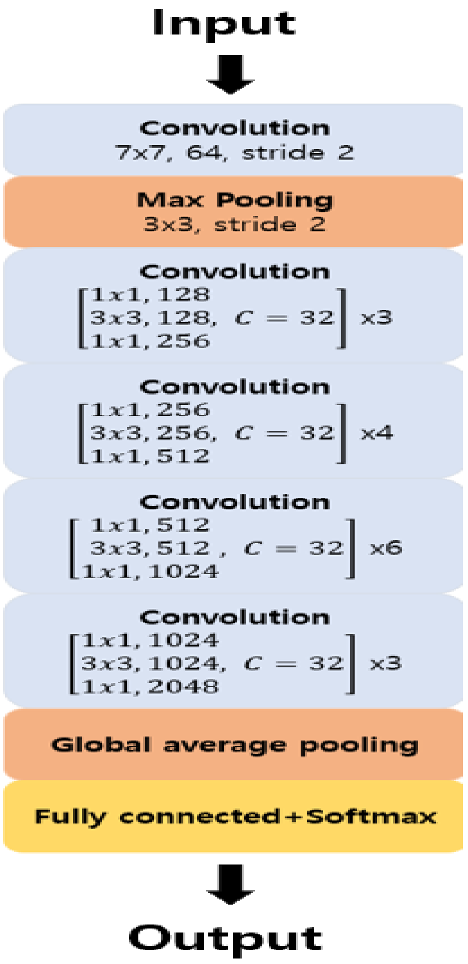
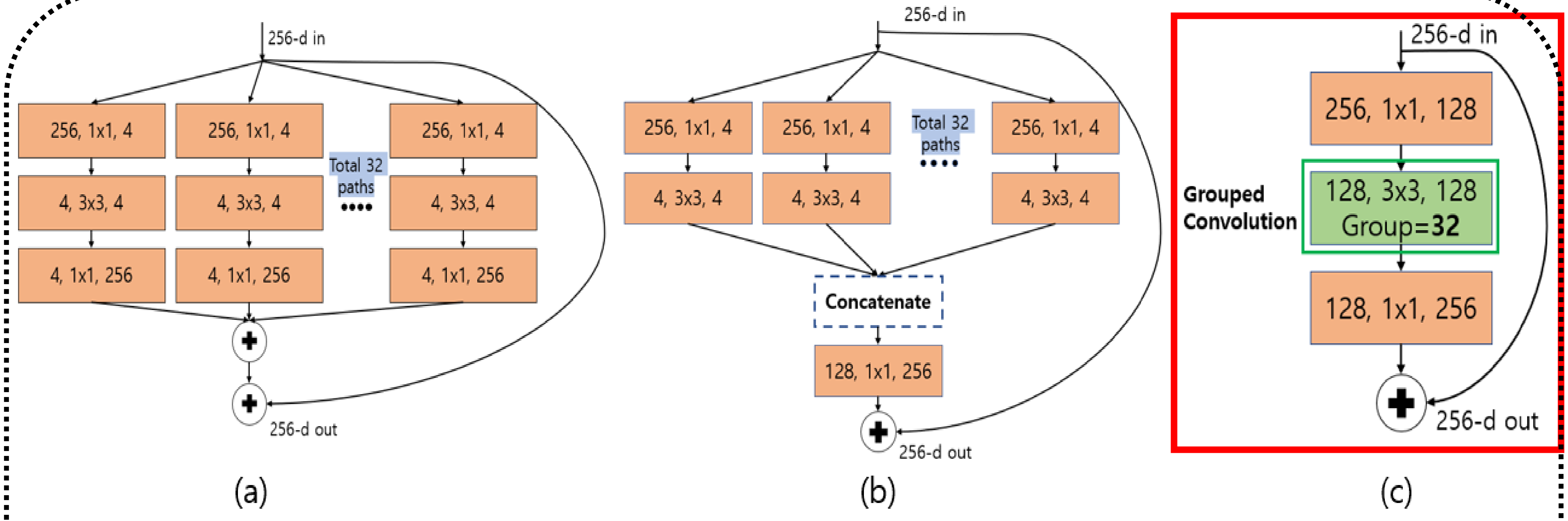
- **Method:**
  - 같은 Spatial map인 경우, block들은 같은 hyper-parameter 공유 **=> <u>Hyper-Parameter 선택 부담감↓</u>**
  - **<u>Grouped convolution</u>** 사용으로 구현을 간단하게 함




**ResNeXt Architecture**

**Fast, Easy Implementation**




Equivalent building blocks of ResNeXt
Performance: (a) = (b) = (c)

**Relations between cardinality(C) and width(d)**

가장 최적의 성능

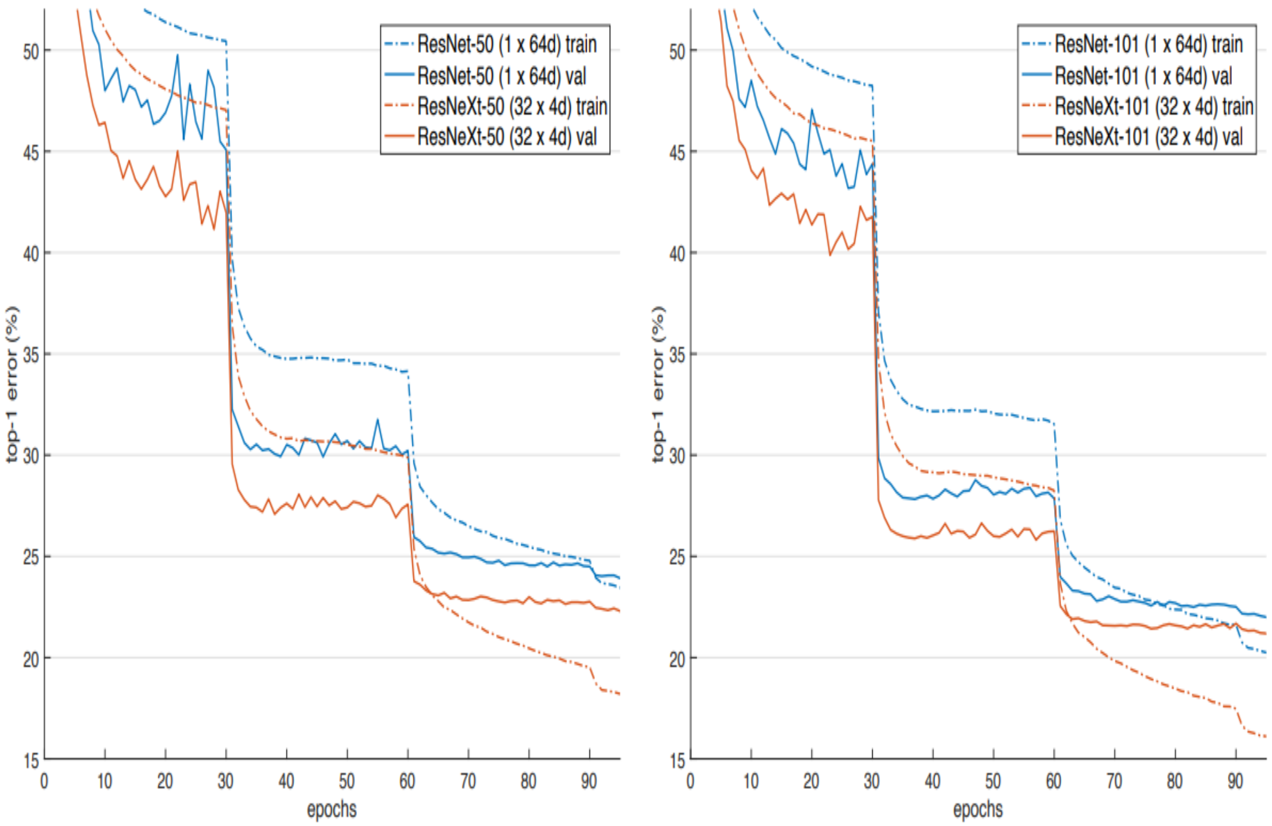
| cardinality $C$ | 1 | 2 | 4 | 8 | 32 |
|---|---|---|---|---|---|
| width of bottleneck $d$ | 64 | 40 | 24 | 14 | 4 |
| width of group conv. | 64 | 80 | 96 | 112 | 128 |

# Aggregated Residual Transformations for Deep Neural Networks (CVPR 2017)

- **Experiment:**

**<u>Cardinality</u>**라는 새로운 차원을 활용해, 기존의 ResNet 보다 더 **<u>좋은 성능을 달성</u>**

**Training curves on ImageNet-1K**




**Ablation experiments on ImageNet-1K**

| | setting | top-1 error (%) |
|---|---|---|
| ResNet-50 | 1 × 64d | 23.9 |
| ResNeXt-50 | 2 × 40d | 23.0 |
| ResNeXt-50 | 4 × 24d | 22.6 |
| ResNeXt-50 | 8 × 14d | 22.3 |
| ResNeXt-50 | 32 × 4d | **22.2** |
| ResNet-101 | 1 × 64d | 22.0 |
| ResNeXt-101 | 2 × 40d | 21.7 |
| ResNeXt-101 | 4 × 24d | 21.4 |
| ResNeXt-101 | 8 × 14d | 21.3 |
| ResNeXt-101 | 32 × 4d | **21.2** |

1. ResNet 보다 ResNeXt가 더 좋은 성능을 보임
2. Cardinality(C)와 width(d)의 설정 값에 따른 비교, 32 x 4d가 가장 좋은 성능을 보임

# Aggregated Residual Transformations for Deep Neural Networks (CVPR 2017)

- **Experiment:**

  **Cardinality**라는 새로운 차원을 활용해, 기존의 ResNet 보다 더 **좋은 성능을 달성**

**Increasing Cardinality vs Deeper/Wider**

| | setting | top-1 err (%) | top-5 err (%) |
|---|---|---|---|
| *1× complexity references:* | | | |
| ResNet-101 | 1 × 64d | 22.0 | 6.0 |
| ResNeXt-101 | 32 × 4d | 21.2 | 5.6 |
| *2× complexity models follow:* | | | |
| ResNet-**200** [15] | 1 × 64d | 21.7 | 5.8 |
| ResNet-101, wider | 1 × **100**d | 21.3 | 5.7 |
| ResNeXt-101 | **2** × 64d | 20.7 | 5.5 |
| ResNeXt-101 | **64** × 4d | **20.4** | **5.3** |

성능: deeper < wider << **Cardinality**

**State-of-the-art models on ImageNet-1K Validation**

| | 224×224 | | 320×320 / 299×299 | |
|---|---|---|---|---|
| | top-1 err | top-5 err | top-1 err | top-5 err |
| ResNet-101 [14] | 22.0 | 6.0 | - | - |
| ResNet-200 [15] | 21.7 | 5.8 | 20.1 | 4.8 |
| Inception-v3 [39] | - | - | 21.2 | 5.6 |
| Inception-v4 [37] | - | - | 20.0 | 5.0 |
| Inception-ResNet-v2 [37] | - | - | 19.9 | 4.9 |
| ResNeXt-101 (**64** × **4d**) | 20.4 | 5.3 | **19.1** | **4.4** |

**한줄평:** 개인적으로, 본 논문은 Network Depth와 Width를 함께 활용한 방법이라 생각함

Cardinality는 결국 convolution을 얼마나 분할할지 나타내는 것 **->** Residual block을 wider하게 만듬