Vision AI

2022 Arxiv Trends

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no.	Paper Title	Research group
1	Pushing the limits of self-supervised ResNets: Can we outperform supervised learning without labels on ImageNet?	DeepMind
2	A ConvNet for the 2020s	FAIR, UC Berkeley
3	OMNIVORE: A Single Model for Many Visual Modalities	Meta AI (Facebook)

Pushing the limits of self-supervised ResNets:
Can we outperform supervised learning without labels on ImageNet?

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Jovana Mitrovic [*1]

https://arxiv.org/pdf/2201.05119.pdf

DeepMind

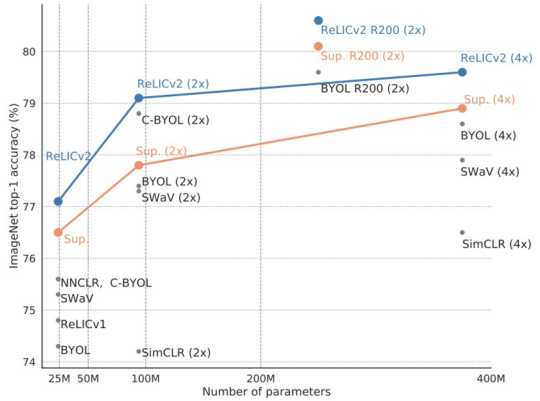


Figure 1. Top-1 linear evaluation accuracy on ImageNet using ResNet50 encoders with 1×, 2× and 4× width multipliers and a ResNet200 encoder with a 2× width multiplier.

ReLICv2

- **Self-supervised methods in representation learning with residual networks.**
- 이전까지의 residual network SSL 은 ImageNet classification benchmark, supervised learning 의 성능을 뛰어넘지 못함.
  - 제안하는 ReLICv2 로 그 성능을 뛰어넘음.

- Combine an explicit invariance loss with a contrastive objective over a varied set of appropriately constructed data view.
  - **invariance loss + contrastive loss 사용.**

- 성능
  - 77.1% top-1 classification accuracy on ImageNet using linear evaluation with a ResNet50.
  - **80.6% with larger ResNet models, outperforming previous SoTA self-supervised approaches.**
  - **First representation learning method to consistently outperform the supervised baseline.**
    - **supervised baseline 을 뛰어넘은 첫 번째 representation learning 기법.**

Representation Learning via Invariant Causal Mechanisms (ReLIC) framework

- Invariant prediction 원칙에 기반하여 representation 학습.
- invariance loss
  - 유사한 포인트와 유사하지 않은 포인트 간의 relationship invariance 계산.
  - Underlying data 의 geometry (기하학적 구조) 의 representations 을 학습.
  - 이러한 속성은 downstream tasks 을 더 잘 수행할 수 있게 representation 학습.

$$\log p(x_i; x_i^+) = \log \frac{e^{\phi_\tau(x_i; x_i^+)}}{e^{\phi_\tau(x_i; x_i^+)} + \sum_{x_i^- \in \mathcal{N}(x_i)} e^{\phi_\tau(x_i; x_i^-)}} \quad (1)$$

ReLIC (Mitrovic et al., 2021) introduces an *invariance loss* defined as the Kullback-Leibler divergence between the likelihood of the anchor point x_i and one of its positives x_i^+ both of which are computed as in equation 1

$$D_{\mathrm{KL}}(p(x_i)|p(x_i^+)) = \mathrm{sg}\left[\mathbb{E}_{p(x_i;x_i^+)} \log p(x_i; x_i^+)\right] - \mathbb{E}_{p(x_i;x_i^+)} \log p(x_i^+; x_i). \quad (2)$$

ReLICv2

기본 목표는 minimize the combination of contrastive negative log likelihood and invariance loss.

1. Better strategies for selecting similar and dissimilar points. 즉, 적절한 positive points, negative points 를 잘 선정함.
2. contrastive loss 와 invariance objectives 통합.

$$\ell_{\mathrm{ReLICv2}}(x_i) = \sum_{x_i^+ \in \mathcal{P}(x_i)} -\alpha \log p(x_i; x_i^+) + \beta D_{\mathrm{KL}}(p(x_i)|p(x_i^+)), \quad (3)$$

ReLICv2

1. Better strategies for selecting similar and dissimilar points.
2. contrastive loss 와 invariance objectives 통합.
    a. minimize the combination of contrastive negative log likelihood and invariance loss.

적절한 positive and negative points 를 select 하는 방법이 ReLIC 과 차이남.

- **Standard SimCLR augmentations + two further augmentation strategies:**
    - **(1) Multi-crop augmentations**
        - 4개의 larger crops (224*224) , 2개의 smaller crops (96*96) 으로 구성. 동일한 이미지에 대해 random crop
    - **(2) Saliency-based background removal**
        - DeepUSPS의 fully unsupervised version 을 사용하여, 이미지의 fg 와 bg 분리. p_{m} = 0.1 의 확률로 random 하게 saliency mask 적용.
        - 이로써, 이미지 object의 위치 representation 학습 가능.
    - **Standard SimCLR augmentations**
        - Random horizontal flip and color distortion
            - Random sequence of brightness, saturation, contrast and hue changes and an optional grayscale conversion.
            - As a final step, Gaussian blur and solarization are applied.

$$\log p(x_i; x_i^+) = \log \frac{e^{\phi_\tau(x_i; x_i^+)}}{e^{\phi_\tau(x_i; x_i^+)} + \sum_{x_i^- \in \mathcal{N}(x_i)} e^{\phi_\tau(x_i; x_i^-)}} \quad (1)$$

$$D_{\mathrm{KL}}(p(x_i)|p(x_i^+)) = \mathrm{sg}\left[\mathbb{E}_{p(x_i; x_i^+)} \log p(x_i; x_i^+)\right] - \mathbb{E}_{p(x_i; x_i^+)} \log p(x_i^+; x_i). \quad (2)$$

$$\ell_{\mathrm{ReLICv2}}(x_i) = \sum_{x_i^+ \in \mathcal{P}(x_i)} -\alpha \log p(x_i; x_i^+) + \beta D_{\mathrm{KL}}(p(x_i)|p(x_i^+)), \quad (3)$$

Results

- Self-supervised learning 에서 ResNet 아키텍처 전반에 걸쳐 SoTA 성능.
- Supervised ResNet50 baseline 보다 성능이 뛰어난 첫 번째 self-supervised representation learning method.
  - 기존의 다른 실험 비교들은 동일한 네트워크 아키텍처를 사용하진 않았음.
  - Not a like-for-like comparison of network architectures.

without needing to change the network architecture. On top-1 classification accuracy on ImageNet RELICv2 achieves 77.1%, 78. with a ResNet50, while with a ResNet200 2× it achieves 80.6%.

1. Linear evaluation on ImageNet

Method	Top-1	Top-5
Supervised (Chen et al., 2020a)	76.5	93.7
SimCLR (Chen et al., 2020a)	69.3	89.0
MoCo v2 (Chen et al., 2020b)	71.1	-
InfoMin Aug. (Tian et al., 2020)	73.0	91.1
BYOL (Grill et al., 2020)	74.3	91.6
RELIC (Mitrovic et al., 2021)	74.8	92.2
SwAV (Caron et al., 2020)	75.3	-
NNCLR (Dwibedi et al., 2021)	75.6	92.4
C-BYOL (Lee et al., 2021)	75.6	92.7
RELICv2 (ours)	**77.1**	93.3

Table 1. Top-1 and top-5 accuracy (in %) under linear evaluation on the ImageNet test for a ResNet50 encoder set for different representation learning methods. For clarity of exposition we only compares against methods which were at one point state-of-art.

2. Semi-supervised training on ImageNet

Method	Top-1		Top-5	
	1%	10%	1%	10%
Supervised (Chen et al., 2020a)	25.4	56.4	48.4	80.4
SimCLR (Chen et al., 2020a)	48.3	65.6	75.5	87.8
BYOL (Grill et al., 2020)	53.2	68.8	78.4	89.00
SwAV (Caron et al., 2020)	53.9	70.2	78.5	89.9
NNCLR (Dwibedi et al., 2021)	56.4	69.8	80.7	89.3
C-BYOL (Lee et al., 2021)	**60.6**	70.5	**83.4**	90.0
RELICv2 (ours)	58.1	**72.4**	81.3	**91.2**

Table 2. Top-1 and top-5 accuracy (in %) after semi-supervised training with a fraction of ImageNet labels on a ResNet50 encoder for different representation learning methods.

Results

3. Transfer to other tasks
- Generality of ReLICv2 representations
- 학습된 features 들이 image domain 전반에 사용 가능한지.

3.3. Transfer to other tasks

We evaluate the generality of RELICv2 representations by testing whether the learned features are useful across image domains.

Classification

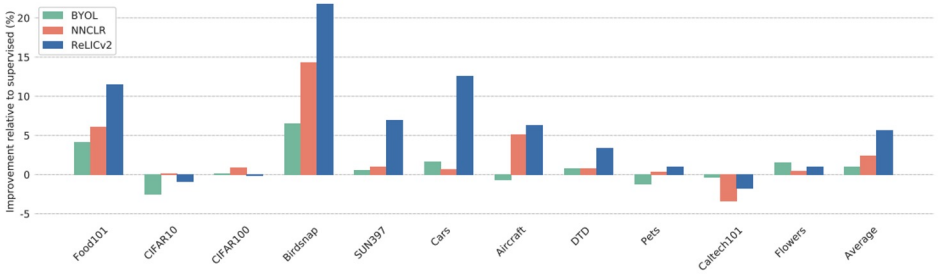


Figure 2. Transfer performance relative to the supervised baseline (a value of 0 indicates equal performance to supervised).

BYOL, NNCLR, ReLICv2 를 representations pre-trained 하여 transfer performance 를 비교
11개 task 중에 ReLICv2 가 7 task 에서 최고 성능을 보임.

Other vision tasks (Semantic segmentation)

Method	PASCAL	Cityscapes
BYOL (Grill et al., 2020)	75.7	74.6
DetCon (Hénaff et al., 2021)	77.3	**77.0**
ReLICv2 (ours)	**77.9**	75.2

On both PASCAL and Cityscapes, RELICv2 outperforms BYOL by a significant margin as can and remarkably, on PASCAL outperforms DetCon (Hénaff et al., 2021) which has been specifically trained for detection.

Results

4. Robustness and OOD generalization

Method	MF	T-0.7	Ti	IN-C
Supervised	65.1	73.9	78.4	40.9
SimCLR (Chen et al., 2020a)	53.2	61.7	68.0	31.1
BYOL (Grill et al., 2020)	62.2	71.6	77.0	42.8
RELIC (Mitrovic et al., 2021)	63.1	72.3	77.7	44.5
RELICv2 (ours)	**65.4**	**74.5**	**79.5**	**44.8**

(a) Datasets testing robustness.

Method	IN-R	IN-S	ObjectNet
Supervised	24.0	6.1	26.6
SimCLR (Chen et al., 2020a)	18.3	3.9	14.6
BYOL (Grill et al., 2020)	23.0	8.0	23.0
RELIC (Mitrovic et al., 2021)	23.8	9.1	23.8
RELICv2 (ours)	**23.9**	**9.9**	**25.9**

(b) Datasets testing OOD generalization.

Table 8. Top-1 Accuracy (in %) under linear evaluation on the ImageNetV2 and ImageNet-C datasets (robustness datasets) and ImageNet-R (IN-R), ImageNet-Sketch (IN-S), ObjectNet (out-of-distribution datasets) for different unsupervised representation learning methods. We evaluate on all three variants on ImageNetv2 – matched frequency (MF), Threshold 0.7 (T-0.7) and Top Images (TI). The results for ImageNet-C (IN-C) are averaged across the 15 different corruptions.

5. Large-scale transfer with JFT-300M

Method	Epochs	Top-1
BYOL (Grill et al., 2020)	1000	67.0
Divide and Contrast (Tian et al., 2021)	1000	67.9
RELICv2 (ours)	1000	**70.3**
BYOL (Grill et al., 2020)	3000	67.6
Divide and Contrast (Tian et al., 2021)	3000	69.8
RELICv2 (ours)	3000	**71.1**
BYOL (Grill et al., 2020)	5000	67.9
Divide and Contrast (Tian et al., 2021)	4500	70.7
RELICv2 (ours)	5000	**71.4**

Table 3. Top-1 accuracy (in %) on ImageNet when learning representations using the JFT-300M dataset. Each method is pre-trained on JFT-300M for an ImageNet-equivalent number of epochs and evaluted on the ImageNet validation set under a linear evaluation protocol.

vision transformers 비교

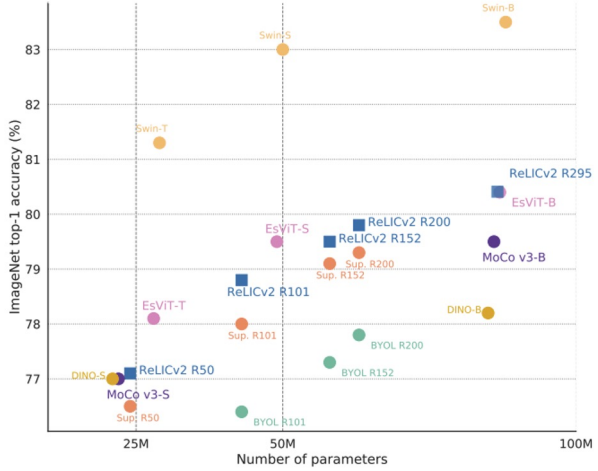


Figure 6. Comparison of ImageNet top-1 accuracy between RELICv2 and recent vision transformer-based architectures (Swin (Liu et al., 2021) represents a fully supervised transformer baseline).

ReLICv2 Pseudo-code

```
'''
f_o: online network: encoder + comparison_net
g_t: target network: encoder + comparison_net
gamma: target EMA coefficient
n_e: number of negatives
p_m: mask apply probability
'''
for x in batch: # load a batch of B samples
    # Apply saliency mask and remove background
    x_m = remove_background(x)
    for i in range(num_large_crops):
        # Select either original or background-removed
        # Image with probability p_m
        x = Bernoulli(p_m) ? x_m : x
        # Do large random crop and augment
        xl_i = aug(crop_l(x))

        ol_i = f_o(xl_i)
        tl_i = g_t(xl_i)

    for i in range(num_small_crops):
        # Do small random crop and augment
        xs_i = aug(crop_s(x))
        # Small crops only go through the online
     network
        os_i = f_o(xs_i)

    loss = 0
    # Compute loss between all pairs of large crops
    for i in range(num_large_crops):
        for j in range(num_large_crops):
            loss += loss_relicv2(ol_i, tl_j, n_e)

    # Compute loss between small crops and large crops
    for i in range(num_small_crops):
        for j in range(num_large_crops):
            loss += loss_relicv2(os_i, tl_j, n_e)
    scale = (num_large_crops + num_small_crops) *
            num_large_crops
    loss /= scale

    # Compute grads, update online and target networks
    loss.backward()
    update(f_o)
    g_t = gamma * g_t + (1 - gamma) * f_o
```

Listing 1. Pseudo-code for RELICv2.

1. 적절한 positive and negative points 를 select 하기 위한 전략
2. 최초로, positive and negative selection 모두에 대한 combine 함.
3. invariance loss 결합하여 사용.

제안한 접근법은 general 하여 특정 positive/negative selection 전략에 특화되어 있지 않음.

A ConvNet for the 2020s

Zhuang Liu[1,2*] Hanzi Mao[1] Chao-Yuan Wu[1] Christoph Feichtenhofer[1] Trevor Darrell[2] Saining Xie[1†]
[1]Facebook AI Research (FAIR) [2]UC Berkeley
Code: https://github.com/facebookresearch/ConvNeXt

https://arxiv.org/pdf/2201.03545v1.pdf

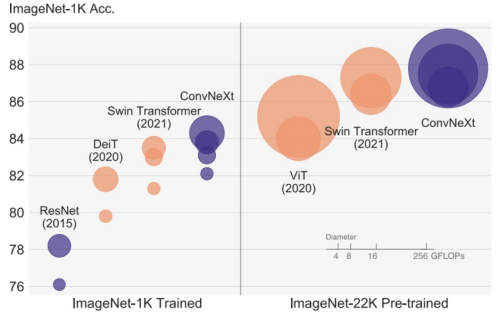
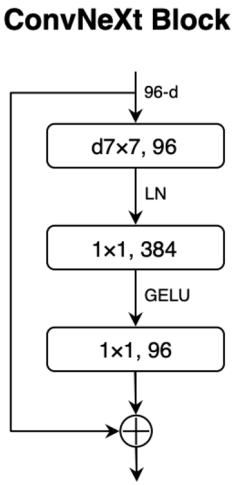


Figure 1. **ImageNet-1K classification** results for • ConvNets and ○ vision Transformers. Each bubble's area is proportional to FLOPs of a variant in a model family. ImageNet-1K/22K models here take 224^2/384^2 images respectively. We demonstrate that a standard ConvNet model can achieve the same level of scalability as hierarchical vision Transformers while being much simpler in design.



<Abstract>

- the effectiveness of hybrid approaches is still largely credited to the intrinsic superiority of Transformers, rather than the inherent inductive biases of convolutions (ex. Swin Transformers)
- **따라서 본 논문에서는 pure ConvNet의 한계를 시험해보겠다! (너의 능력을 보여줘! 느낌)**
  ViT 이전의 ConvNet과 ViT 이후의 ConvNet 의 gap 을 잇는 bridge ⇒ pure ConvNet 이 어디까지 할 수 있는지?
- How do design decisions in Transformers impact ConvNets' performance?
  Transformer 에서 가진 디자인을 ConvNet 에 적용시킨다면, 성능을 더 끌어올릴 수 있지 않을까?
- **ConvNeXt: Constructed entirely from standard ConvNet modules, 새로운 CNN 아키텍처**
  - achieving 87.8% ImageNet top-1 accuracy
  - outperforming Swin Transformers on COCO detection and ADE20K segmentation
  - maintaining the simplicity and efficiency of standard ConvNets

https://arxiv.org/pdf/2201.03545v1.pdf

Modernizing a ConvNet

- ResNet-50 / Swin-T / FLOPs around 4.5×10^9 (주로 비교)
- ResNet-200 / Swin-B / FLOPs around 15.0 × 10^9

Network Modernization

1. Training Techniques: Applying similar training techniques used to train ViT and obtain much improved results compared to the original ResNet-50
   a. 최신의 ViT 테크닉을 resnet-50 에 적용
2. macro design
3. ResNeXt
   a. resnet -> resnext 의 테크닉 적용
4. inverted bottleneck
5. large kernel size
6. various layer-wise micro designs.

1. Training Techniques

- Training epochs: 300 epochs (기존 ResNets: 90 epochs. 더 길게 학습.)
- Optimizer: AdamW
- Data augmentation
  - Mixup
  - Cutmix
  - RandAugment
  - Random Erasing
- Regularization
  - Stochastic Depth
  - Label Smoothing
- This training recipe increased the performance of the ResNet-50 model from **76.1% to 78.8%(+2.7%)**

2. Macro Design : Changing stage compute ratio

- Swin-T's computation ratio of each stage: 1:1:3:1
- larger than Swin-T: 1:1:9:1
- ConvNeXt :
  - 기존 resnet 50 의 각 Stage 안의 block 수가 (3,4,6,4) 이었는데,
  - following the design 하여 the number of blocks in each stage: (3, 3, 9, 3) 으로 바꿈.
  - **The accuracy: 78.8% ⇒ 79.4% (+0.6%)**
  - ***we will use this stage compute ratio.***

C: number of channels
B: number of blocks

- ConvNeXt-T: $C = (96, 192, 384, 768), B = (3, 3, 9, 3)$
- ConvNeXt-S: $C = (96, 192, 384, 768), B = (3, 3, 27, 3)$
- ConvNeXt-B: $C = (128, 256, 512, 1024), B = (3, 3, 27, 3)$
- ConvNeXt-L: $C = (192, 384, 768, 1536), B = (3, 3, 27, 3)$
- ConvNeXt-XL: $C = (256, 512, 1024, 2048), B = (3, 3, 27, 3)$

2. Macro Design : Changing stem to "Patchify"

* Stem : 네트워크 처음 들어가는 부분. ⇒ patchify 형태로 바꾸겠다.

- ResNet: The stem cell in standard ResNet: 7×7 convolution layer with stride 2, followed by a max pool (results in a 4×4 downsampling of the input images)
- VIT: "patchify" strategy is used as the stem cell, which corresponds to a large kernel size (e.g. kernel size = 14 or 16) and non-overlapping convolution.
- **Swin Transformer: uses a similar "patchify" layer, but with a smaller patch size of 4 (architecture's multi-stage 때문에)**
- **ConvNeXt: ResNet-style stem cell with a patchify layer implemented using a 4x4, stride 4 convolution layer**
  - ConvNeXt 에서 patchify 를 4*4, stride 4 convolution layer 사용.
- **The accuracy: 79.4% ⇒ 79.5%**
- ***We will use the "patchify stem" (4×4 non-overlapping convolution) in the network.***

3. ResNeXt-ify

- ResNeXt's guiding principle: "use more groups, expand width" : **ResNeXt 에서 group convolution 사용.**
  - 그룹 (cardinality) 을 많이 나누고, 대신에 width (channel) 를 늘려라
- **ConvNeXt: uses depthwise convolution (극단적으로 한다. 그룹 수=256),** a special case of grouped convolution where the number of groups equals the number of channels, ⇒ 연산량이 감소. (group convolution 을 극단적으로 사용) ⇒ depth wise convolution 과 동일.
  increases the network width to the same number of channels as Swin-T's (from 64 to 96)
- **The network performance to 80.5% with increased FLOPs (5.3G)**
  - 그룹을 나누면서 채널을 늘렸더니, FLOPs 가 약간 증가함.
- ***We will now employ the ResNeXt design.***

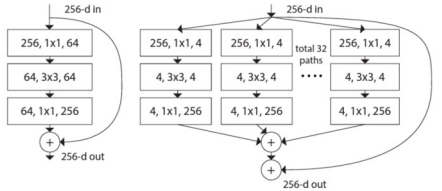


Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

- ResNeXt의 핵심은 ResNet 구조의 Architecture에 Inception에서 사용하던 Cardinality 개념을 도입하여 Convolution 연산을 쪼개서 진행하고, 서로 다른 Weight를 구한뒤 합쳐주는 Split-Transform-Merge를 추가한 것이다.
- 이 때, 쪼개진 CNN이 몇개의 path를 가지는지를 결정하는 하이퍼파라미터가 바로 Cardinality이며, 각각의 path에서 가지는 채널을 depth라고 정의한다.
- 따라서 위 그림은, Conv2 Stage 기준 32개의 path와 4의 사이즈를 가지므로, Cardinality = 32, detph = 4의 ResNeXt-50 (32x4d)로 정의할 수 있다.

4. Inverted Bottleneck

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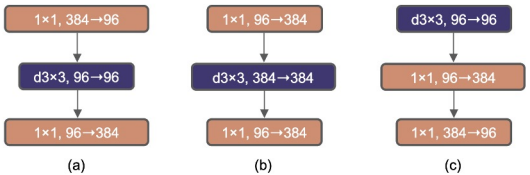
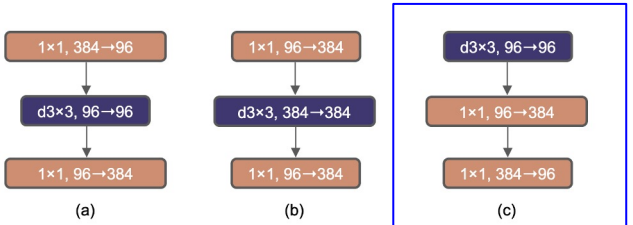


Figure 3. **Block modifications and resulted specifications. (a)** is a ResNeXt block; in **(b)** we create an inverted bottleneck block and in **(c)** the position of the spatial depthwise conv layer is moved up.

- **results: reduces the whole network FLOPs to 4.6G, slightly improved performance, 80.5% ⇒ 80.6%**
- ***We will now use inverted bottlenecks***



실제 사용되는 inverted block

Figure 3. **Block modifications and resulted specifications. (a)** is a ResNeXt block; in **(b)** we create an inverted bottleneck block and in **(c)** the position of the spatial depthwise conv layer is moved up.

5. Large Kernel Sizes : Moving up depthwise conv layer

- To explore large kernels, 한 가지 전제조건은 **depthwise conv layer의 위치를 위로 이동하는 것** (Transformers에서 확인가능)
- The MSA block 이 MLP layers 보다 앞선다.
  - MSA (multihead self-attention) 은 depthwise conv layer (3*3) 와 동일한 역할.
  - MSA 가 먼저 하고 MLP layer 를 사용하는 것처럼 depthwise conv layer 를 사용하는 것이 자연스럽다.
- **results: reduces the FLOPs to 4.1G, resulting in a temporary performance degradation to 79.9%.**

5. Large Kernel Sizes : Increasing the kernel size

- experimented with several kernel sizes, including 3, 5, 7, 9, and 11.
- The network's performance increases from 79.9% (3x3) to **80.6% (7x7),** while the network's FLOPs stay roughly the same
- **results: performance increases from 79.9% (3*3) to 80.6% (7*7) while the network's FLOPs stay roughly the same.**
- ***We will use 7×7 depthwise conv in each block***

6. Micro Design : Replacing ReLU with GELU

- Activation functions을 Gaussian Error Linear Unit (GELU)사용 (ReLU대신) ⇒ can be thought of as a smoother variant of ReLU
  - Google's BERT, and OpenAI's GPT-2, and, most recently, ViTs
- **ReLU can be substituted with GELU in ConvNet, although the accuracy stays unchanged (80.6%).**

6. Micro Design : Fewer activation functions

- Transformer와 ResNet의 차이: Transformers have fewer activation functions.
- 1x1 conv을 포함한 각 convolutional layer에 activation function을 추가하는 것이 일반적이나,
- **ConvNeXt는 Transformer block의 스타일을 복제하여 두 개의 1x1 layer 사이에 있는 layer을 제외한 나머지 블록에서 모든 GELU layer을 제거.**
- **Result: Increasing 0.7% (81.3%), practically matching the performance of Swin-T.**

6. Micro Design : Fewer normalization layers

- Transformer blocks: usually have fewer normalization layers
- ConvNeXt는 두 개의 BN(BatchNorm) layer을 제거하여 **1x1 layer 앞에 하나의 BN layer만 남김**
- **The accuracy: 81.3% ⇒ 81.4%, surpassing Swin-T's result.**

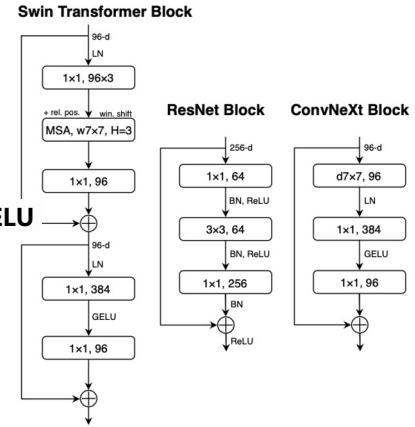


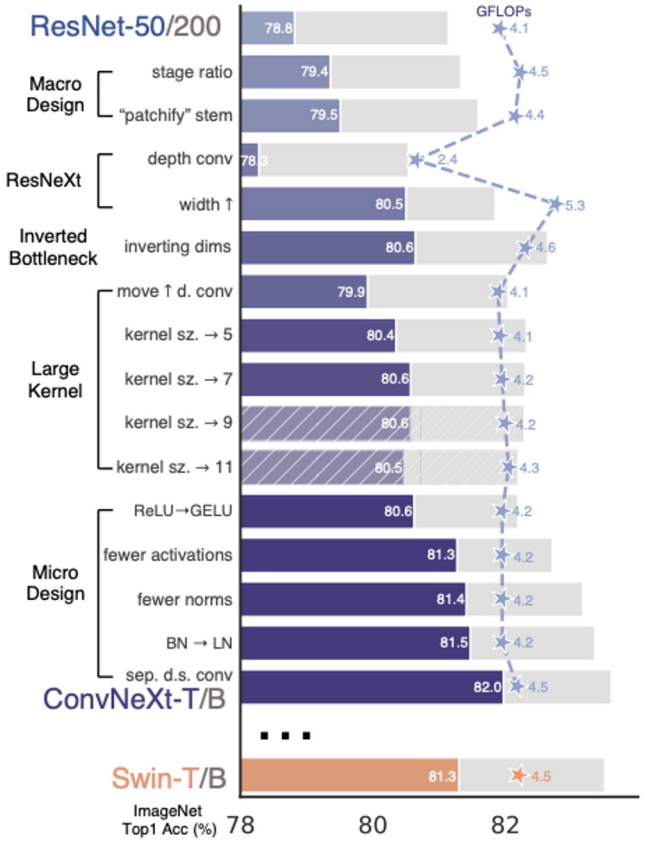
Figure 4. **Block designs** for a ResNet, a Swin Transformer, and a ConvNeXt. Swin Transformer's block is more sophisticated due to the presence of multiple specialized modules and two residual connections. For simplicity, we note the linear layers in Transformer MLP blocks also as "1×1 convs" since they are equivalent.

6. Micro Design : Substituting BN with LN

- **BN보다 Layer Normalization(LN)** has been used in Transformers (좋은 성능 나옴)
- 오리지널 ResNet에서 LN을 BN으로 직접 대체하면 성능이 좋지는 않으나, **ConvNeXt 모델은 LN을 사용한 training에 문제 없음**
- **The accuracy: 81.4% ⇒ 81.5%**

6. Micro Design :Separate downsampling layers

- In ResNet: is achieved by the residual block at the start of each stage, using 3x3 conv with stride 2 (1x1 conv with stride 2 at the shortcut connection)
- In Swin T: a separate downsampling layer is added between stages
  - **stage 사이에 따로 downsampling layer 존재.**
- ConvNeXt: uses **2x2 conv layers with stride 2 for spatial downsampling** and **adding normalization layers** wherever spatial resolution is changed
- **The accuracy: 81.5% ⇒ 82% (Swin T 상당히 능가)**



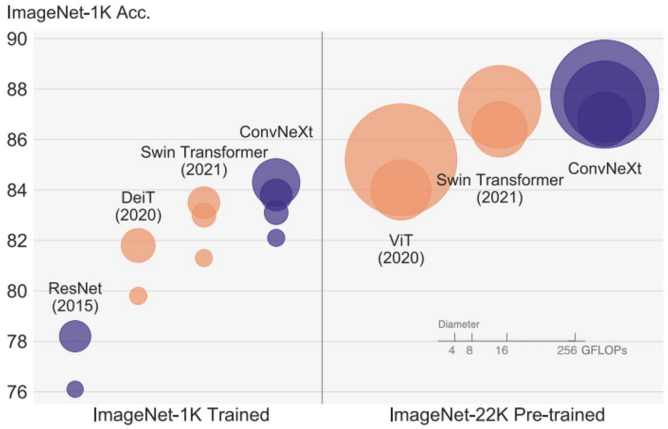


Figure 1. **ImageNet-1K classification** results for • ConvNets and ○ vision Transformers. Each bubble's area is proportional to FLOPs of a variant in a model family. ImageNet-1K/22K models here take 224^2/384^2 images respectively. We demonstrate that a standard ConvNet model can achieve the same level of scalability as hierarchical vision Transformers while being much simpler in design.

Results – ImageNet-1K

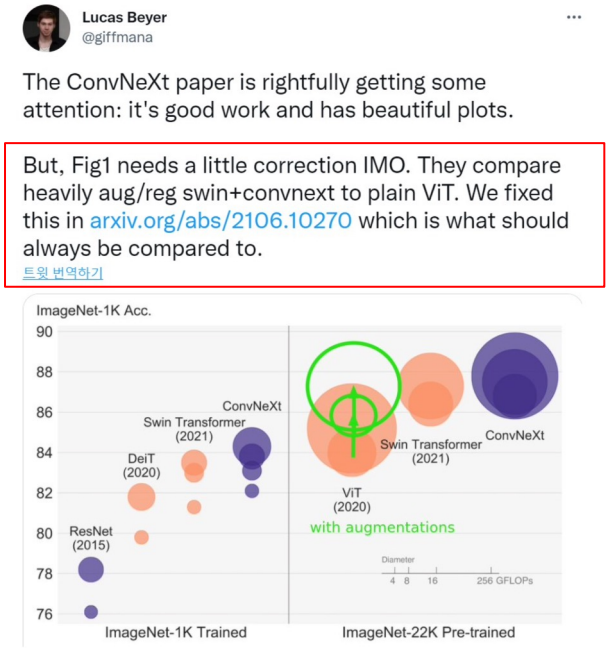
model	image size	#param.	FLOPs	throughput (image / s)	IN-1K top-1 acc.
ImageNet-1K trained models					
• RegNetY-4G [51]	224^2	21M	4.0G	1156.7	80.0
• RegNetY-8G [51]	224^2	39M	8.0G	591.6	81.7
• RegNetY-16G [51]	224^2	84M	16.0G	334.7	82.9
• EffNet-B3 [67]	300^2	12M	1.8G	732.1	81.6
• EffNet-B4 [67]	380^2	19M	4.2G	349.4	82.9
• EffNet-B5 [67]	456^2	30M	9.9G	169.1	83.6
• EffNet-B6 [67]	528^2	43M	19.0G	96.9	84.0
• EffNet-B7 [67]	600^2	66M	37.0G	55.1	84.3
○ DeiT-S [68]	224^2	22M	4.6G	978.5	79.8
○ DeiT-B [68]	224^2	87M	17.6G	302.1	81.8
○ Swin-T	224^2	28M	4.5G	757.9	81.3
• ConvNeXt-T	224^2	29M	4.5G	774.7	**82.1**
○ Swin-S	224^2	50M	8.7G	436.7	83.0
• ConvNeXt-S	224^2	50M	8.7G	447.1	**83.1**
○ Swin-B	224^2	88M	15.4G	286.6	83.5
• ConvNeXt-B	224^2	89M	15.4G	292.1	**83.8**
○ Swin-B	384^2	88M	47.1G	85.1	84.5
• ConvNeXt-B	384^2	89M	45.0G	95.7	**85.1**
• ConvNeXt-L	224^2	198M	34.4G	146.8	**84.3**
• ConvNeXt-L	384^2	198M	101.0G	50.4	**85.5**

Results – ImageNet-22K

ImageNet-22K pre-trained models					
• R-101x3 [36]	384^2	388M	204.6G	-	84.4
• R-152x4 [36]	480^2	937M	840.5G	-	85.4
○ ViT-B/16 [18]	384^2	87M	55.5G	93.1	84.0
○ ViT-L/16 [18]	384^2	305M	191.1G	28.5	85.2
○ Swin-B	224^2	88M	15.4G	286.6	85.2
• ConvNeXt-B	224^2	89M	15.4G	292.1	**85.8**
○ Swin-B	384^2	88M	47.0G	85.1	86.4
• ConvNeXt-B	384^2	89M	45.1G	95.7	**86.8**
○ Swin-L	224^2	197M	34.5G	145.0	86.3
• ConvNeXt-L	224^2	198M	34.4G	146.8	**86.6**
○ Swin-L	384^2	197M	103.9G	46.0	87.3
• ConvNeXt-L	384^2	198M	101.0G	50.4	**87.5**
• ConvNeXt-XL	224^2	350M	60.9G	89.3	**87.0**
• ConvNeXt-XL	384^2	350M	179.0G	30.2	**87.8**

Table 1. **Classification accuracy on ImageNet-1K.** Similar to Transformers, ConvNeXt also shows promising scaling behavior with higher-capacity models and a larger (pre-training) dataset. Inference throughput is measured on a V100 GPU, following [42]. On an A100 GPU, ConvNeXt can have a much higher throughput than Swin Transformer. See Appendix E.

Google Brain

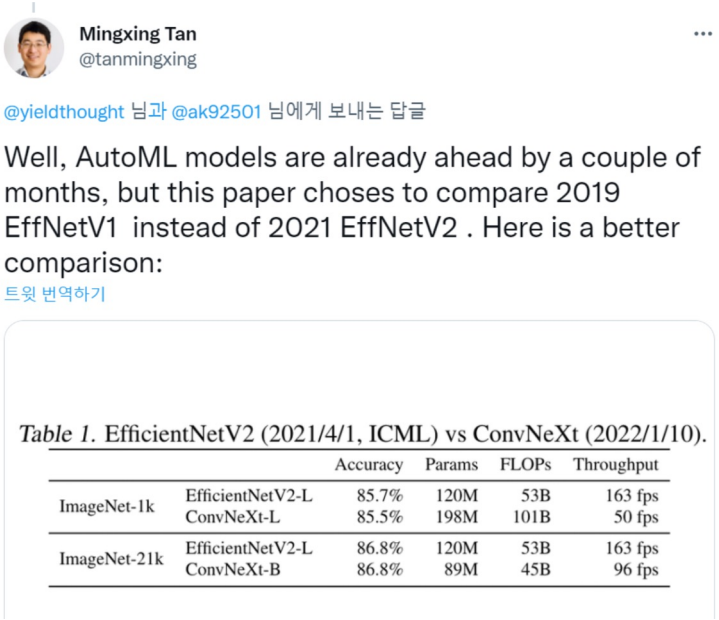


Lucas Beyer
@giffmana

The ConvNeXt paper is rightfully getting some attention: it's good work and has beautiful plots.

But, Fig1 needs a little correction IMO. They compare heavily aug/reg swin+convnext to plain ViT. We fixed this in arxiv.org/abs/2106.10270 which is what should always be compared to.

트윗 번역하기



Mingxing Tan
@tanmingxing

@yieldthought 님과 @ak92501 님에게 보내는 답글

Well, AutoML models are already ahead by a couple of months, but this paper choses to compare 2019 EffNetV1 instead of 2021 EffNetV2 . Here is a better comparison:

트윗 번역하기

Table 1. EfficientNetV2 (2021/4/1, ICML) vs ConvNeXt (2022/1/10).

		Accuracy	Params	FLOPs	Throughput
ImageNet-1k	EfficientNetV2-L	85.7%	120M	53B	163 fps
	ConvNeXt-L	85.5%	198M	101B	50 fps
ImageNet-21k	EfficientNetV2-L	86.8%	120M	53B	163 fps
	ConvNeXt-B	86.8%	89M	45B	96 fps

Isotropic ConvNeXt vs. ViT

model	#param.	FLOPs	throughput (image / s)	training mem. (GB)	IN-1K acc.
○ ViT-S	22M	4.6G	978.5	4.9	79.8
● ConvNeXt-S (*iso.*)	22M	4.3G	1038.7	4.2	79.7
○ ViT-B	87M	17.6G	302.1	9.1	81.8
● ConvNeXt-B (*iso.*)	87M	16.9G	320.1	7.7	82.0
○ ViT-L	304M	61.6G	93.1	22.5	82.6
● ConvNeXt-L (*iso.*)	306M	59.7G	94.4	20.4	82.6

Table 2. **Comparing isotropic ConvNeXt and ViT.** Training memory is measured on V100 GPUs with 32 per-GPU batch size.

Results – **Object Detection** and **Segmentation** on COCO, **Semantic Segmentation** on ADE20K

backbone	FLOPs	FPS	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	AP^{mask}	AP^{mask}_{50}	AP^{mask}_{75}
Mask-RCNN 3× schedule								
○ Swin-T	267G	23.1	46.0	68.1	50.3	41.6	65.1	44.9
● ConvNeXt-T	262G	25.6	**46.2**	67.9	50.8	**41.7**	65.0	44.9
Cascade Mask-RCNN 3× schedule								
● ResNet-50	739G	11.4	46.3	64.3	50.5	40.1	61.7	43.4
● X101-32	819G	9.2	48.1	66.5	52.4	41.6	63.9	45.2
● X101-64	972G	7.1	48.3	66.4	52.3	41.7	64.0	45.1
○ Swin-T	745G	12.2	50.4	69.2	54.7	43.7	66.6	47.3
● ConvNeXt-T	741G	13.5	**50.4**	69.1	54.8	**43.7**	66.5	47.3
○ Swin-S	838G	11.4	51.9	70.7	56.3	45.0	68.2	48.8
● ConvNeXt-S	827G	12.0	**51.9**	70.8	56.5	**45.0**	68.4	49.1
○ Swin-B	982G	10.7	51.9	70.5	56.4	45.0	68.1	48.9
● ConvNeXt-B	964G	11.4	**52.7**	71.3	57.2	**45.6**	68.9	49.5
○ Swin-B‡	982G	10.7	53.0	71.8	57.5	45.8	69.4	49.7
● ConvNeXt-B‡	964G	11.5	**54.0**	73.1	58.8	**46.9**	70.6	51.3
○ Swin-L‡	1382G	9.2	53.9	72.4	58.8	46.7	70.1	50.8
● ConvNeXt-L‡	1354G	10.0	**54.8**	73.8	59.8	**47.6**	71.3	51.7
● ConvNeXt-XL‡	1898G	8.6	**55.2**	74.2	59.9	**47.7**	71.6	52.2

Table 3. **COCO object detection and segmentation results** using Mask-RCNN and Cascade Mask-RCNN. ‡ indicates that the model is pre-trained on ImageNet-22K. ImageNet-1K pre-trained Swin results are from their Github repository [3]. AP numbers of the ResNet-50 and X101 models are from [42]. We measure FPS on an A100 GPU. FLOPs are calculated with image size (1280, 800).

backbone	input crop.	mIoU	#param.	FLOPs
ImageNet-1K pre-trained				
○ Swin-T	512^2	45.8	60M	945G
● ConvNeXt-T	512^2	**46.7**	60M	939G
○ Swin-S	512^2	49.5	81M	1038G
● ConvNeXt-S	512^2	**49.6**	82M	1027G
○ Swin-B	512^2	49.7	121M	1188G
● ConvNeXt-B	512^2	**49.9**	122M	1170G
ImageNet-22K pre-trained				
○ Swin-B‡	640^2	51.7	121M	1841G
● ConvNeXt-B‡	640^2	**53.1**	122M	1828G
○ Swin-L‡	640^2	53.5	234M	2468G
● ConvNeXt-L‡	640^2	**53.7**	235M	2458G
● ConvNeXt-XL‡	640^2	**54.0**	391M	3335G

Table 4. **ADE20K validation results** using UperNet [80]. ‡ indicates IN-22K pre-training. Swins' results are from its GitHub repository [2]. Following Swin, we report mIoU results with multi-scale testing. FLOPs are based on input sizes of (2048, 512) and (2560, 640) for IN-1K and IN-22K pre-trained models, respectively.

OMNIVORE: A Single Model for Many Visual Modalities

Rohit Girdhar* Mannat Singh* Nikhila Ravi* Laurens van der Maaten Armand Joulin Ishan Misra*
Meta AI
https://facebookresearch.github.io/omnivore

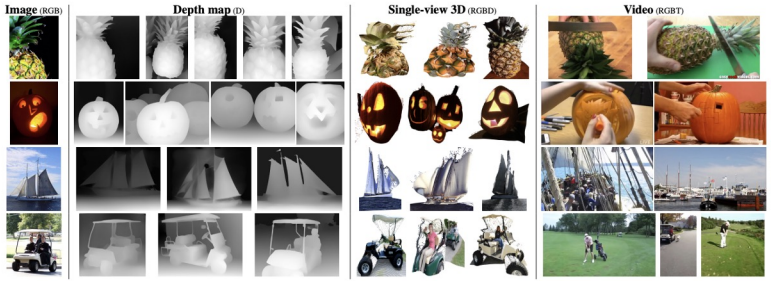


Figure 1. OMNIVORE is a single vision model for many different visual modalities. It learns to construct representations that are aligned across visual modalities, without requiring training data that specifies correspondences between those modalities. Using OMNIVORE's shared visual representation, we successfully identify nearest neighbors of **left:** an image (ImageNet-1K validation set) in vision datasets that contain **right:** depth maps (ImageNet-1K training set), single-view 3D images (ImageNet-1K training set), and videos (Kinetics-400 validation set).

https://arxiv.org/pdf/2201.08377v1.pdf

- Meta AI (https://github.com/facebookresearch/omnivore)
- **'OMNIVORE' model**
- **three different visual modalites: Images, videos, and single-view 3D ⇒ 하나의 single model 학습.**
  - flexibility of transformer-based architecture (각 Model does not use a custom architecture)
- off-the shelf standard dataset 사용
  - ImageNet 1k, Kinetics, SUN RGB-D
- 같은 사이즈의 modality specific model 보다 좋은성능

Contribution

1. being able to perform cross-modal generalization
2. able to save the research and engineering effort dedicated to optimizing models for a particular task
3. **this model is naturally multi-model that can leverage new visual sensors as they become available**

OMNIVORE Model

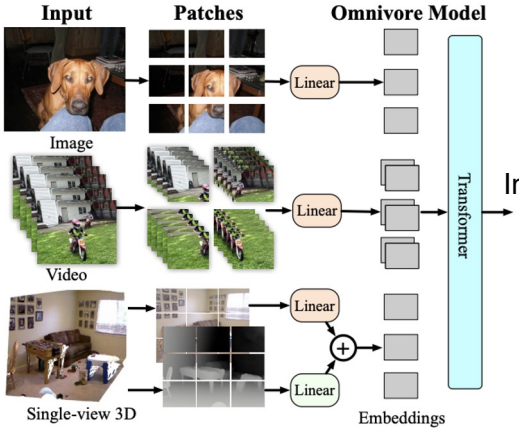
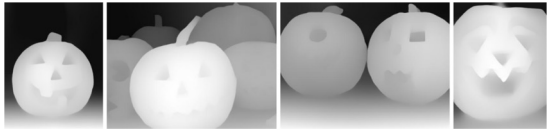


Figure 2. Multiple visual modalities in the OMNIVORE model. We convert image, video, and single-view 3D modalities into embeddings that are fed into a Transformer model. The images are converted into patches, videos into spatio-temporal tubes, and the single-view 3D images are converted into RGB patches and depth patches. The patches are projected into embeddings using linear layers. We use the same linear layer for (image or video) RGB patches and a separate one for depth patches.

Image - RGB (ImageNet-1k)

Video - RGBT (Kinetics-400)



Depthmap + Single-view 3D (RGBD)

Model Architecture

- visual modality 끼리는 최대한 parameter sharing 하도록 디자인
  - **RGB ⇒ same layer to embedding**
  - **depth는 따로 embedding 해서 add it to RGB patch (Linear LN layer)**
- Swin Transformer
- Self-attention
- Relative Position Encoding

Experiments (Eval)

1. transfer dataset

Dataset	Task	#cls	#train	#val
iNaturalist-2018 (iNat18) [36]	Fine-grained cls.	8142	437K	24K
Oxford-IIIT Pets (Pets) [67]	Fine-grained cls.	37	3.6K	3.6K
Places-365 (P365) [100]	Scene cls.	365	1.8M	36K
Something Something-v2 (SSv2) [31]	Action cls.	174	169K	25K
EPIC-Kitchens-100 (EK100) [20]	Action cls.	3806	67K	10K
NYU-v2 (NYU) [63]	Scene cls.	10	794	653
NYU-v2-seg (NYU-seg) [63]	Segmentation	40	794	653

Table 1. Transfer datasets used to evaluate OMNIVORE on image, video and single-view 3D modalities. The table reports the task, number of classes (#cls), number of training samples (#train), and number of validation samples (#val) for each dataset.

- off-the shelf standard dataset 사용 (pre-train)
  - ImageNet 1k, Kinetics, SUN RGB-D

2. modality-specific models와 비교했을 때 비슷하거나 성능 개선
   - same model architecture and number of parameter

Method	ImageNet-1K top-1	ImageNet-1K top-5	Kinetics-400 top-1	Kinetics-400 top-5	SUN top-1
ImageSwin-T [49]	**81.2**	95.5	✗	✗	✗
VideoSwin-T [50]	✗	✗	78.8	93.6	✗
DepthSwin-T	✗	✗	✗	✗	**63.1**
OMNIVORE (Swin-T)	80.9	**95.5**	**78.9**	**93.8**	62.3
ImageSwin-S [49]	83.2	96.2	✗	✗	✗
VideoSwin-S [50]	✗	✗	80.6	94.5	✗
DepthSwin-S	✗	✗	✗	✗	**64.9**
OMNIVORE (Swin-S)	**83.4**	**96.6**	**82.2**	**95.4**	64.6
ImageSwin-B [49]	83.5	96.5	✗	✗	✗
VideoSwin-B [50]	✗	✗	80.6	94.6	✗
DepthSwin-B	✗	✗	✗	✗	64.8
OMNIVORE (Swin-B)	**84.0**	**96.8**	**83.3**	**95.8**	**65.4**

Table 2. OMNIVORE *vs.* modality-specific models that have the same model architecture and number of parameters. OMNIVORE is a single model trained from scratch jointly on the IN1K, K400 and SUN datasets whereas the modality-specific models are trained specifically for each dataset (modality). The ImageSwin model is trained from scratch while the VideoSwin and DepthSwin models are finetuned from the ImageSwin model. OMNIVORE performs at-par or outperforms modality-specific models.

Experiments (Eval)

3. downstream task fine-tuning 시 model 성능. better performance

Model	Method	P365		iNat18		Pets		SSv2		EK100		NYU	NYU-seg
		top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	top-5	top-1	mIoU
Swin-T	Specific	57.9	87.3	**69.7**	87.6	93.7	99.6	62.2	88.7	41.8	62.8	72.5	47.9
	OMNIVORE	**58.2**	**87.4**	69.0	**87.7**	**94.2**	**99.7**	**64.4**	**89.7**	**42.7**	**63.1**	**77.0**	**49.7**
Swin-S	Specific	58.7	**88.1**	72.9	90.2	94.4	99.6	66.8	91.1	42.5	63.4	**76.7**	51.3
	OMNIVORE	**58.8**	88.0	**73.6**	**90.8**	**95.2**	**99.7**	**68.2**	**91.8**	**44.9**	**64.8**	**76.7**	**52.7**
Swin-B	Specific	58.9	**88.3**	73.2	90.9	94.2	99.7	65.8	90.6	42.8	64.0	76.4	51.1
	OMNIVORE	**59.2**	**88.3**	**74.4**	**91.1**	**95.1**	**99.8**	**68.3**	**92.1**	**47.4**	**67.7**	**78.8**	**54.0**

Table 3. Comparing OMNIVORE with modality-specific models after finetuning the models on seven downstream tasks. Results are presented for three different model sizes: T, S, and B. Our image specific model is pretrained on IN1K. The video specific and single-view 3D specific models are both initialized using inflation from the pretrained image-specific model and fine-tuned on K400 and SUN RGB-D respectively. OMNIVORE models are at par with or outperform modality-specific models on nearly all downstream tasks.

Experiments (Eval)

4. 3개의 data type (ImageNet1K, Kinetics, SUN) task (SoTA)와 비교하더라도 advanced model 과 동등한 성능 or better performance (볼드체 어디갔지?)

Method	ImageNet-1K top-1	ImageNet-1K top-5	Kinetics-400 top-1	Kinetics-400 top-5	SUN top-1
MViT-B-24 [24]	83.1	-	✗	✗	✗
ViT-L/16 [21]	85.3	-	✗	✗	✗
ImageSwin-B [49]	85.2	97.5	✗	✗	✗
ImageSwin-L [49]	86.3	97.9	✗	✗	✗
ViT-B-VTN [64]	✗	✗	79.8	94.2	✗
TimeSformer-L [8]	✗	✗	80.7	94.7	✗
ViViT-L/16x2 320 [5]	✗	✗	81.3	94.7	✗
MViT-B 64×3 [24]	✗	✗	81.2	95.1	✗
VideoSwin-B [50]	✗	✗	82.7	95.5	✗
VideoSwin-L [50]	✗	✗	83.1	95.9	✗
DF^{2}Net [48]	✗	✗	✗	✗	54.6
G-L-SOOR [77]	✗	✗	✗	✗	55.5
TRecgNet [22]	✗	✗	✗	✗	56.7
CNN-RNN [9]	✗	✗	✗	✗	60.7
Depth Swin-B	✗	✗	✗	✗	69.1
Depth Swin-L	✗	✗	✗	✗	68.7
OMNIVORE (Swin-B)	85.3	97.5	84.0	96.2	67.2
OMNIVORE (Swin-L)	86.0	97.7	84.1	96.3	67.1

Table 4. Comparing OMNIVORE with state-of-the-art models on the image, video, and single-view 3D classification datasets used to pre-train OMNIVORE. OMNIVORE performs on par with or better than state-of-the-art models on all three pre-training tasks, including modality-specific models of similar size.

5. Image classification fine tuning 실험에서의 sota model과 비교

Method	P365	iNat18	Pets
EfficientNet B6 [92]	58.5	79.1	95.4
EfficientNet B7 [92]	58.7	80.6	–
EfficientNet B8 [92]	58.6	81.3	–
DeiT-B [84] ↑	–	79.5	–
ViT-B/16 [21] ↑	58.2	79.8	–
ViT-L/16 [21] ↑	59.0	81.7	–
OMNIVORE (Swin-B)	59.3	76.3	95.5
OMNIVORE (Swin-B ↑)	59.6	82.6	95.9
OMNIVORE (Swin-L)	59.4	78.0	95.7
OMNIVORE (Swin-L ↑)	**59.9**	**84.1**	**96.1**

Table 5. Comparing OMNIVORE with state-of-the-art models in image classification finetuning experiments on three datasets. OMNIVORE representations generalize well to scene classification (P365) and fine-grained classification (iNat18, Pets). ↑ indicates finetuning on a higher resolution image (384 × 384px; see [85]).

정리

- **다양한 visual modalities 를 이용하여 모델 성능 향상 (Potential)**
- **하지만 몇가지 limitation 존재**
  1. OMNIVORE just perform **on single-view 3D images**; it doesn't generalize to other 3D delegations (i,e voxels, point clouds..)
  2. Only perform on **visual data** (not co-occuring modalities like audio)
  3. using only classification and structured prediction tasks.

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