ICLR 2021
AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

2022.08.03

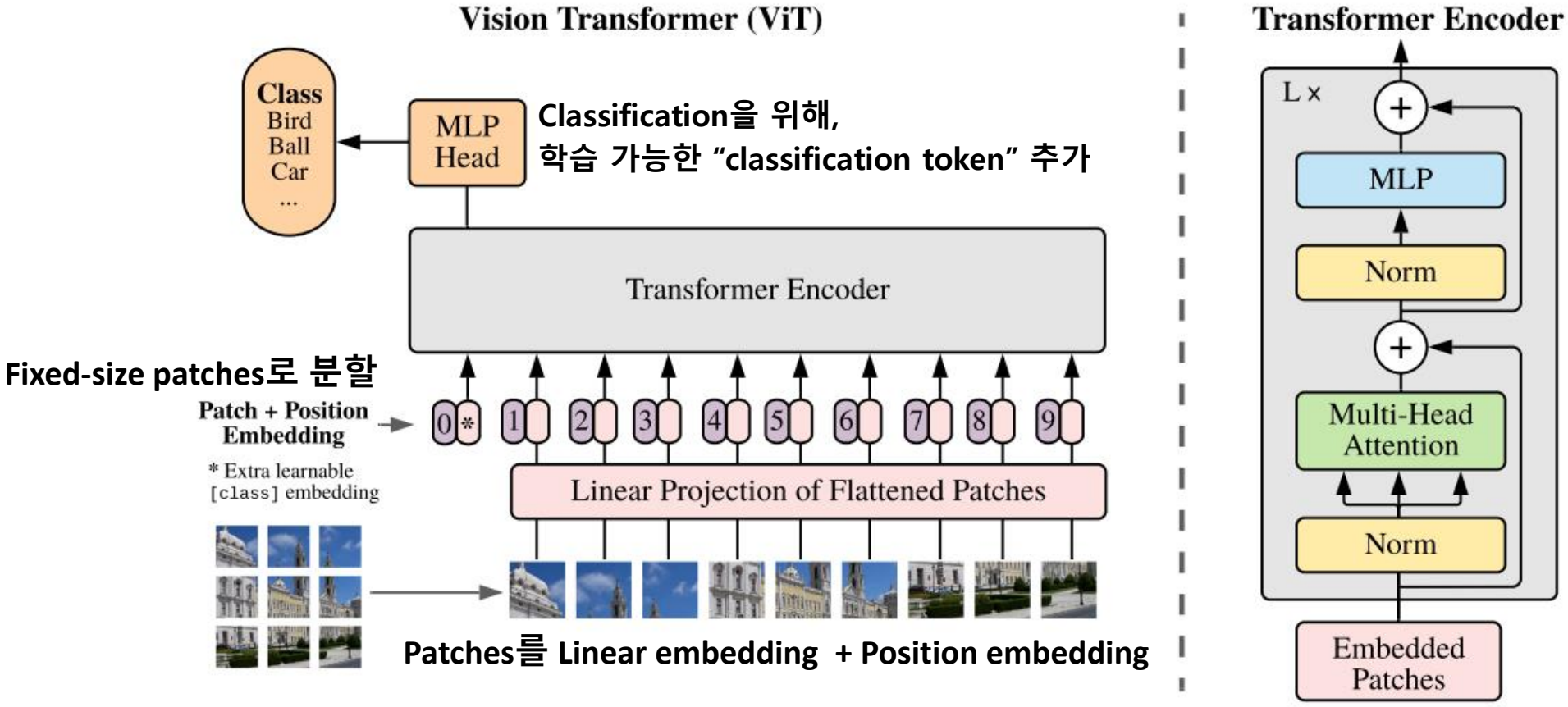
논문 리뷰

배성훈

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

- **Research Background:**
  - 기존의 CV 연구에 NLP의 Transformer를 적용 (CNN 사용 X)
  - 그러나 Transformer가 translation equivariance 와 locality 같은 CNN 고유의 일부 inductive biases가 부족해 **불충분한 양의 데이터를 학습할 때 쉽지 않은 일반화**
  - 이를 **large scale training**이 해결 가능. 충분한 양의 사전 학습!

최대한 Standard transformer를 그대로 이미지에 적용하고자 함.



AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

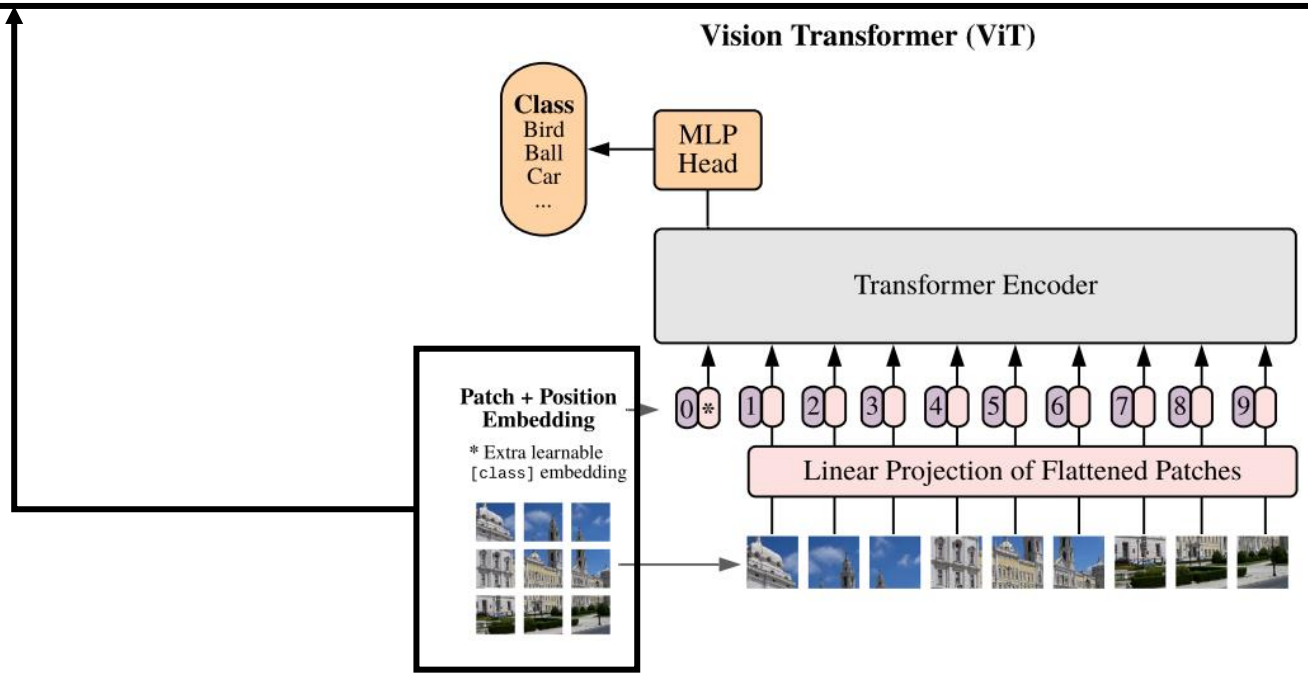
- **Method:**

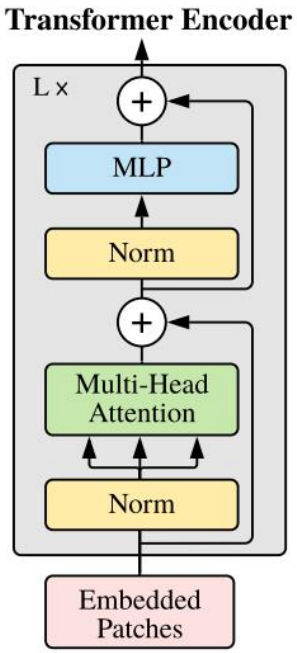
<Input>

- 일반적인 Transformer는 token embedding에 대한 1차원의 sequence를 입력으로 받음
- 2차원의 이미지를 다루기 위해 논문은 3차원 이미지를 **flatten된 2차원 patch의 sequence로 변환**

$$\mathbf{x} \in \mathbb{R}^{\underbrace{\mathbf{H \times W \times C}}_{\text{3차원}}} \rightarrow \mathbf{x}_p \in \mathbb{R}^{\underbrace{N \times \left(P^2 \times C\right)}_{\text{2차원}}}$$

(H, W) = original image resolution, C = number of channel
(P, P) = image patch size
N = number of patch = HW/P^2





AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

- **Method:**

<Embedding Sequence Patch>

- Transformer는 input으로 **1D sequence of token embeddings**를 가지기 때문에 image patch (2D images)를 Flatten한 후 학습 가능한 linear projection을 사용해 **D 차원에 mapping**
- BERT의 CLS token과 비슷하게, Transformer encoder (z_L^0) 의 output이 image representation y 역할을 하도록 만듬

$y = LN(z_L^0)$

$Layernorm(LN)$

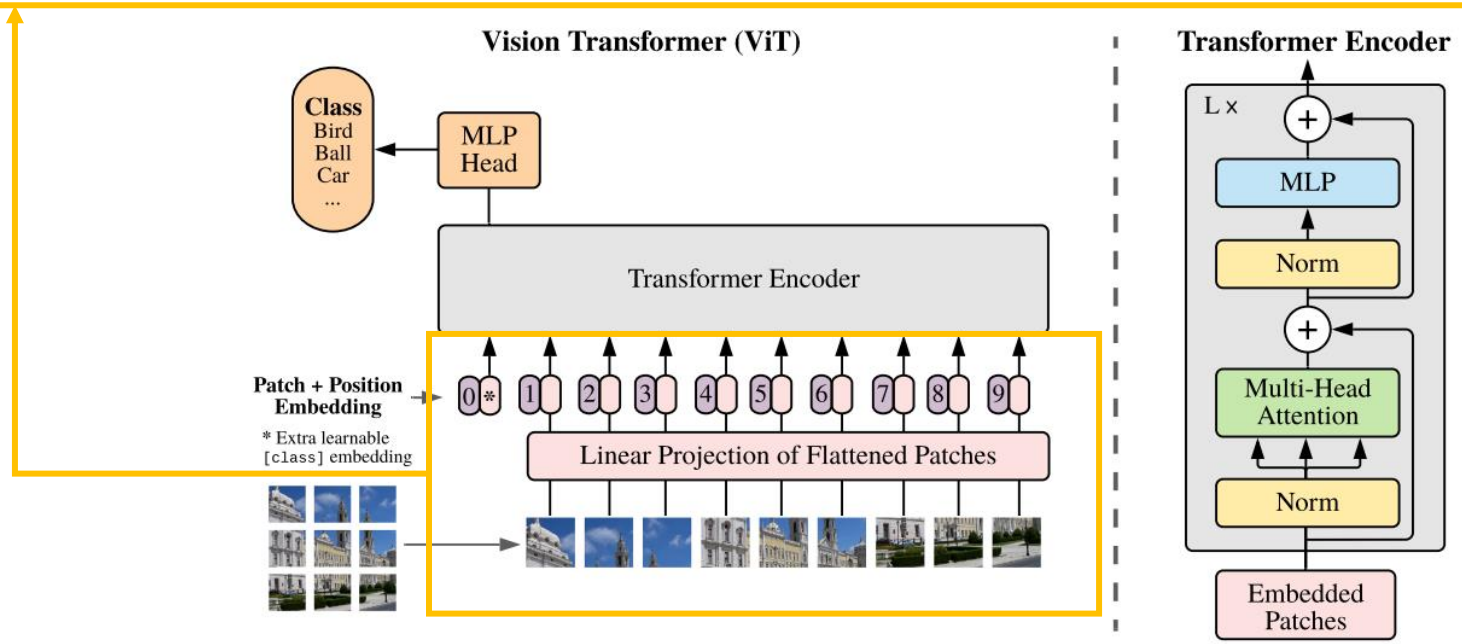
Embedding Sequence Patch

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1\mathbf{E}; \mathbf{x}_p^2\mathbf{E}; \cdots; \mathbf{x}_p^N\mathbf{E}] + \mathbf{E}_{pos}, \qquad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \ \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D}$$

Trainable class token embedding 추가

Position embeddings

각각의 **Patch embedding + Position embedding**
위치 정보를 활용
학습 가능한 1차원의 embedding을 사용



AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

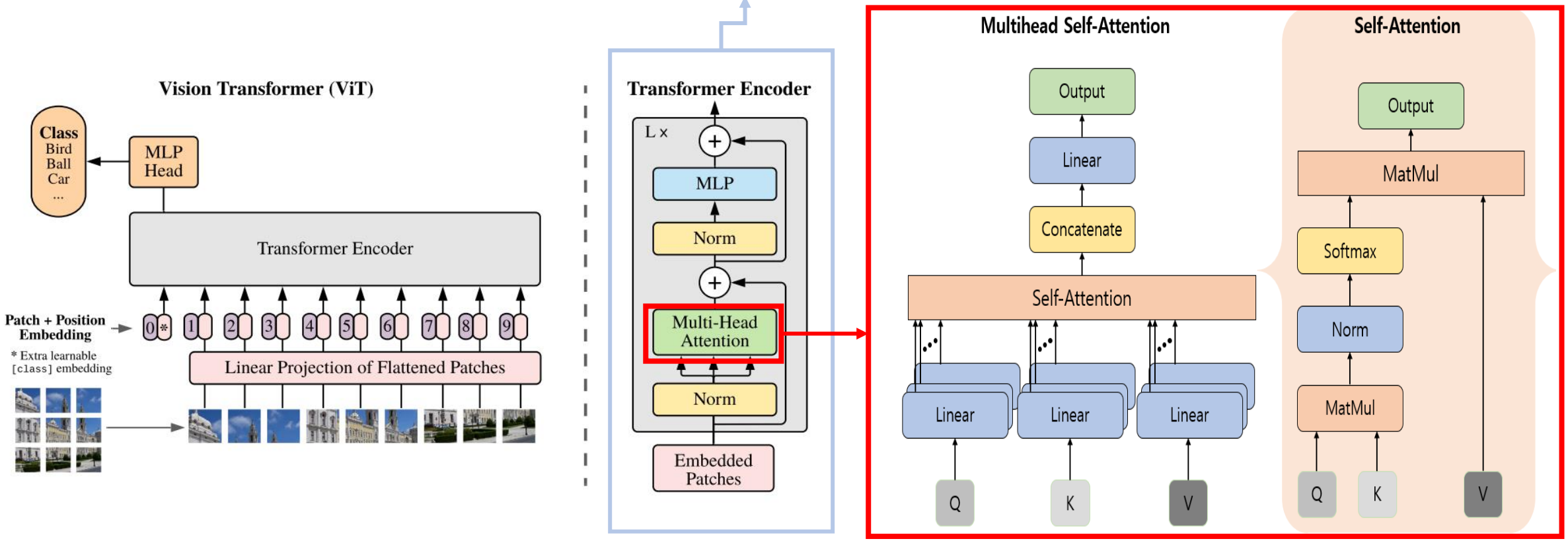
- **Method:**

<Transformer Encoder>

- **Multihead Self-Attention (MSA) + MLP**
- Layernorm(LN)은 모든 block 앞에 적용, 모든 block의 뒤에는 Residual connection이 추가
- 여기서 MLP는 GELU 비선형성을 갖는 2개의 layer를 포함

$$\mathbf{z}'_\ell = \mathrm{MSA}(\mathrm{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \qquad \ell = 1 \ldots L$$

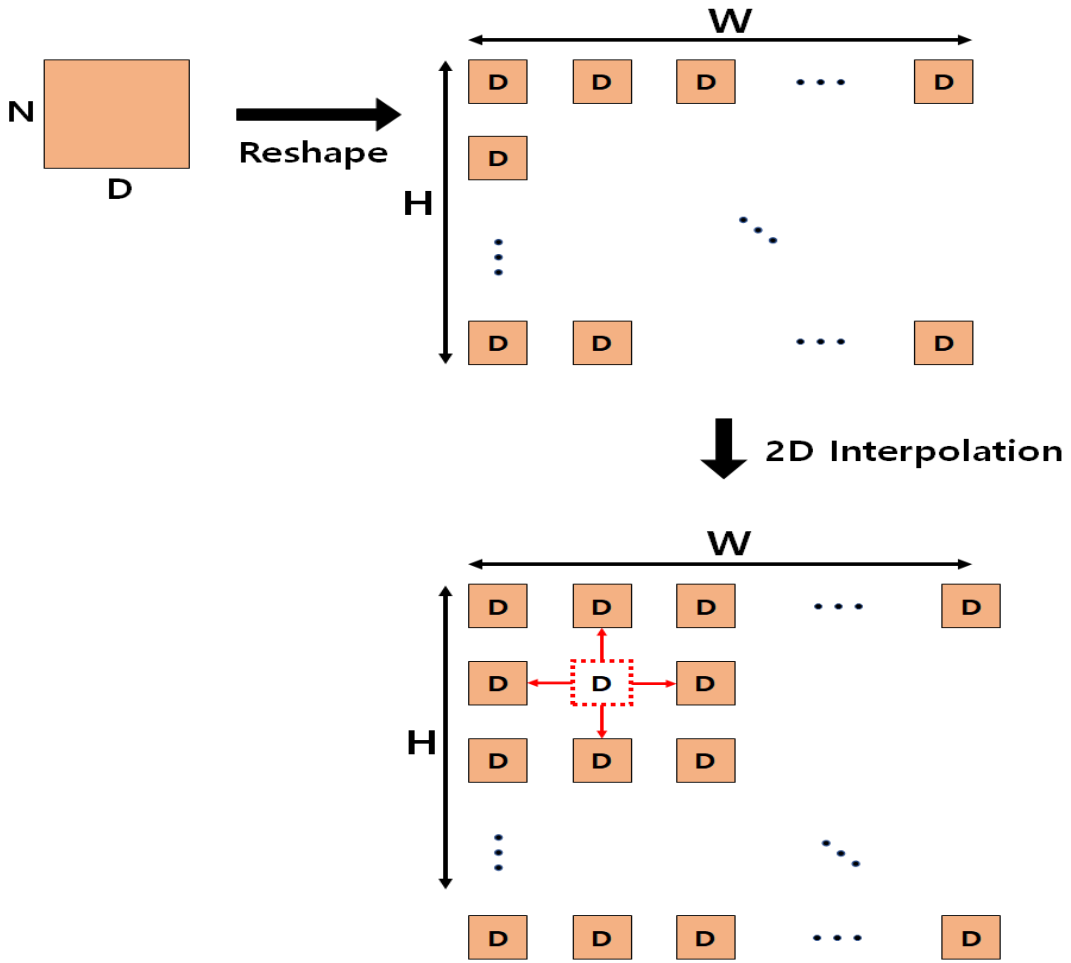
$$\mathbf{z}_\ell = \mathrm{MLP}(\mathrm{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \qquad \ell = 1 \ldots L$$



AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

- **Method: <Fine tunning and Higher resolution>**
  - ViT는 대량의 데이터셋에 대해 사전 학습한 후 더 작은 downstream tasks에 fine-tunning을 하는 방법을 취함
  - Fine-Tunning 시 사전 학습된 prediction head를 제거하고, 0으로 초기화된 DxK FC layer를 부착 **(K= Downstream class의 개수)**

2D Interpolation when fine tunning



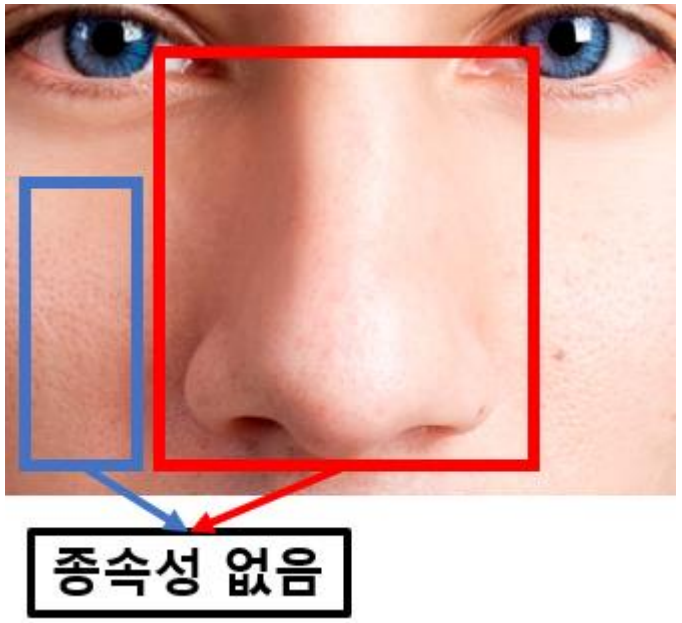
사전학습 시보다 **더 높은 해상도의 이미지**로 Fine-tunning하는 것이 더 **좋은 결과** 가져옴

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

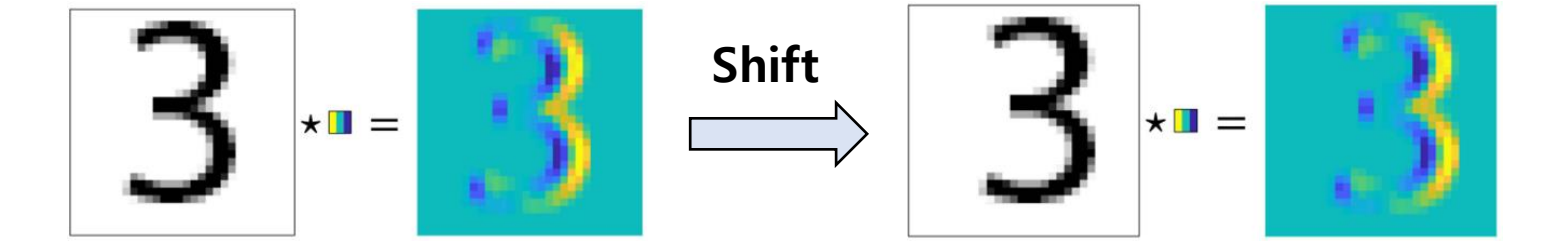
- **Method: <Inductive bias>**
  - Self-attention으로 이루어진 ViT는 CNN에 비해 더 작은 image-specific **inductive bias**를 가짐

    *대표적인 **Inductive bias**
    1. **Locality** (Neighborhood 픽셀이 가까울수록 영향도가 커짐)
    2. **Translation Invariant** (object가 x, y축으로 이동하거나 회전해도 같은 object 인식)

    적은 Inductive bias: Optimal parameter를 찾기 위한 space가 커져 데이터가 충분하지 않으면 학습이 잘 안됨
  - ViT는 이를 해결하기 위해 **large datasets**(ex. 14M-300M images)로 **pretrained** 시켜 이를 사용해 specific task with fewer datapoints에 transfer learning을 함



Locality



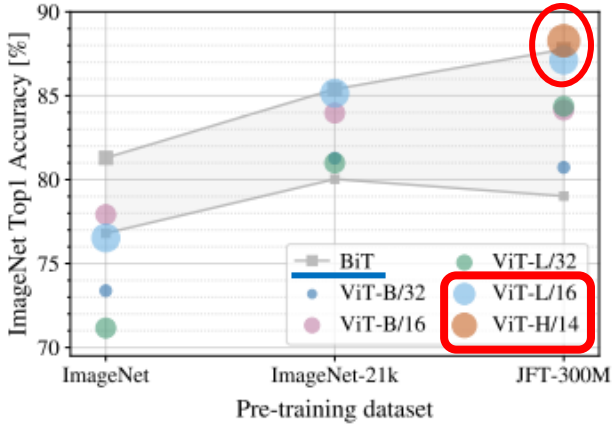
Output of Conv layer (shift equivariant) **Output of Conv layer (shift equivariant)**

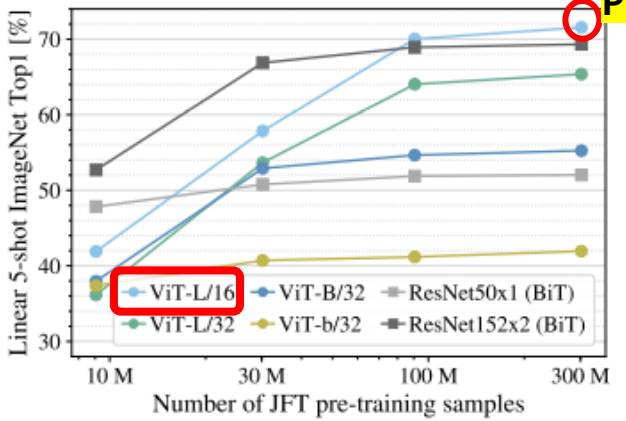
Translation Invariant

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

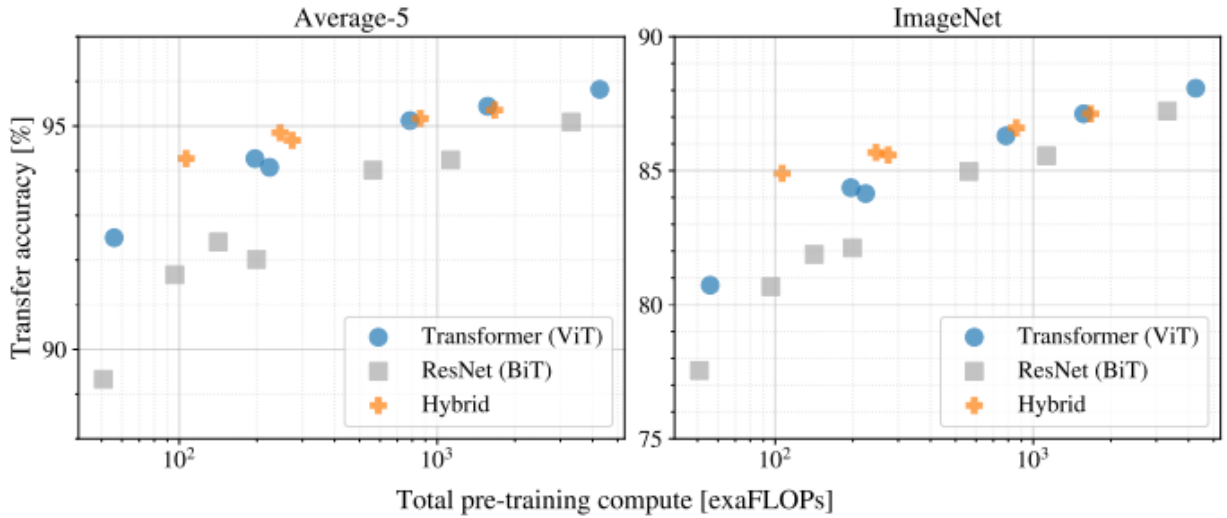
- **Experiment:**
  - 실험결과, 사전 학습된 데이터가 적을수록 성능이 안 좋아짐
  - 즉, ViT는 사전 학습된 데이터가 많아야 좋은 성능을 보임

ViT를 pretraining할 때 사용하는 데이터 셋의 크기에 따른 결과 비교





Pretrained dataset ↑ => Performance ↑



모델들의 scale을 맞춘 후에 성능 비교 (Scale 지표: FLOPS)

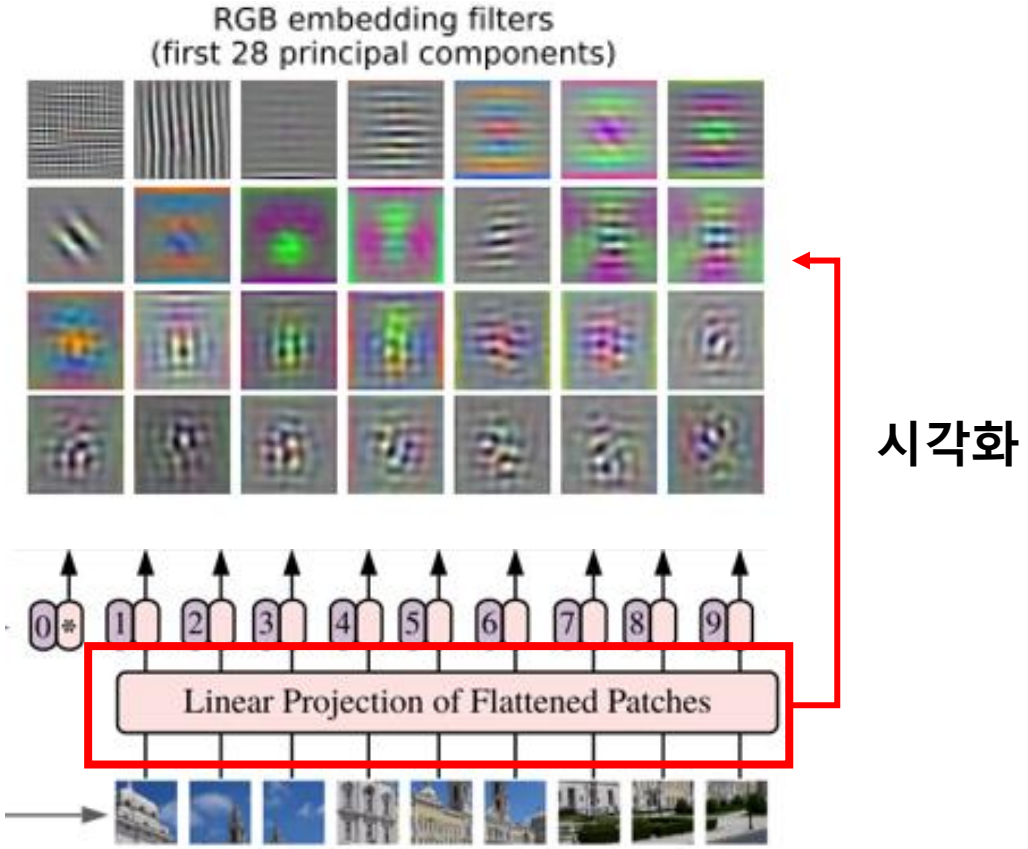
ViT vs ResNet(BiT)

Better Performance/compute trade off

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

- **Experiment:**
  - 첫 번째 Linear Projection 부분에서 주요 요소 28개를 선정해 시각화
  - Embedding filter를 시각화 했을 때 CNN filter 와 비슷한 기능을 보임 (**많은 데이터를 사전학습한 경우**)
  - CNN과 같이 이미지 인식에 필수인 Edge, Color 등의 low-level feature들을 잘 포착

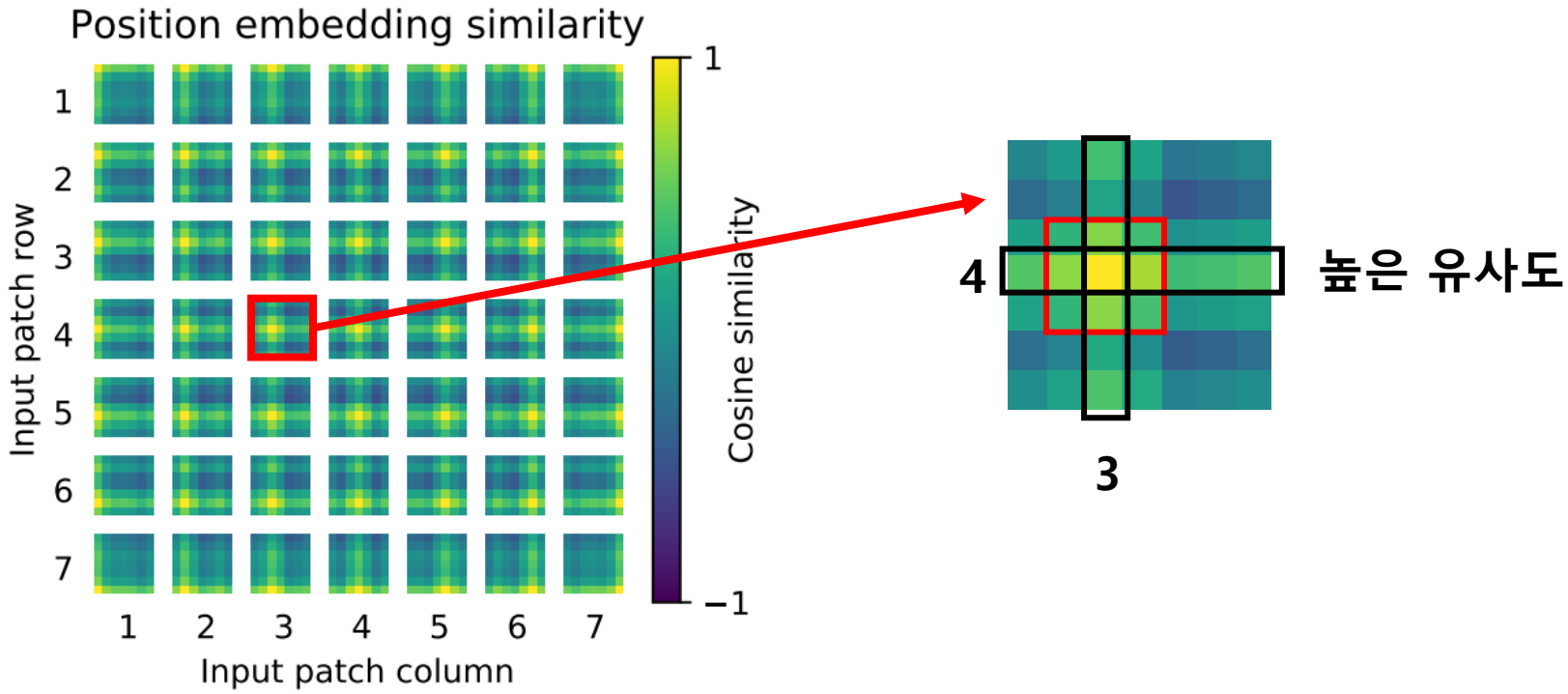
Embedding Projection



AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

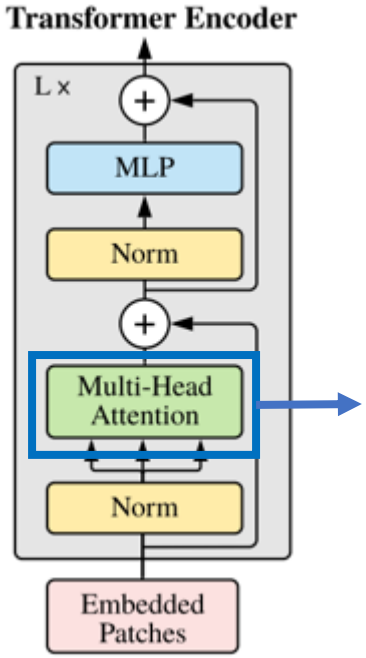
- **Experiment:**
  - **가까운 거리, 같은 열 또는 행**에 위치한 Patch는 **비슷한 position embedding과 높은 유사도**를 보임

Position Embedding

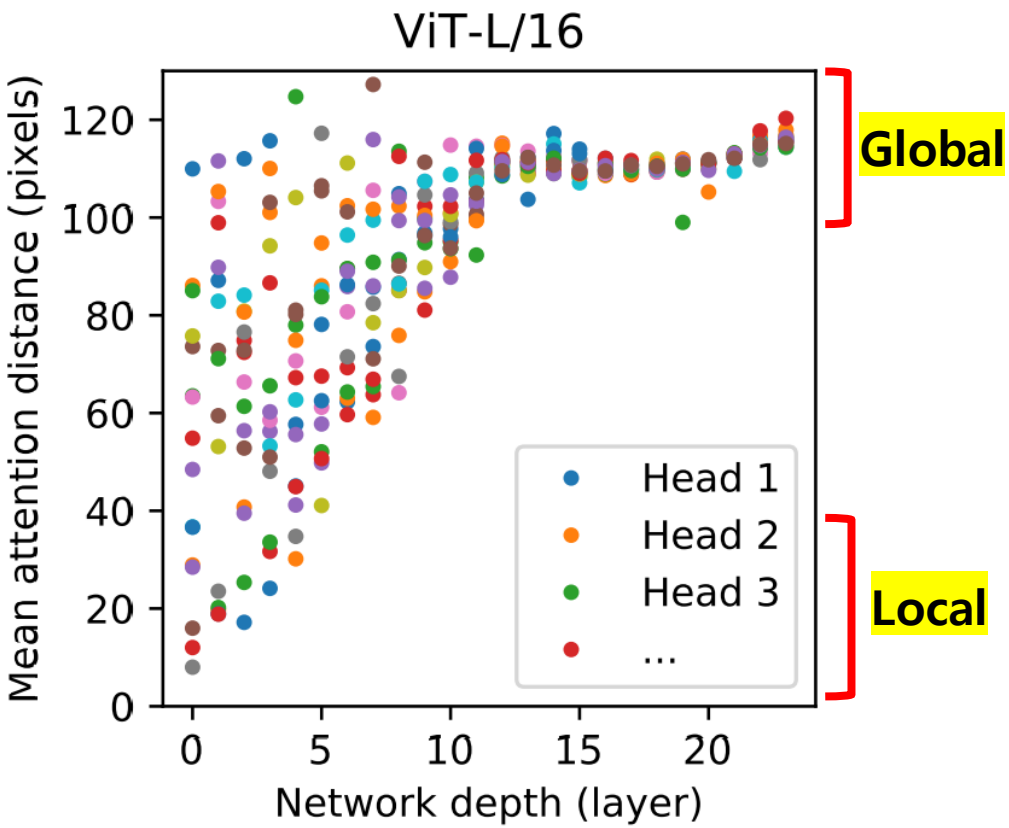


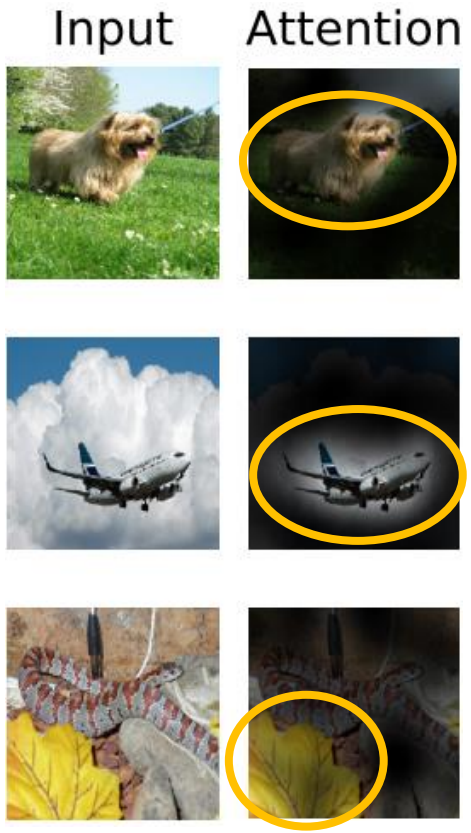
AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

- **Experiment:**
  - Attention Distance는 CNN의 Receptive Field와 유사한 개념
  - Self-Attention은 네트워크가 가장 첫 번째 layer에서도 이미지의 Global features 파악
  - Attention Distance를 시각화한 결과 첫 번째 layer에서부터 **Local, Global features 잘 포착**



Attention Distance





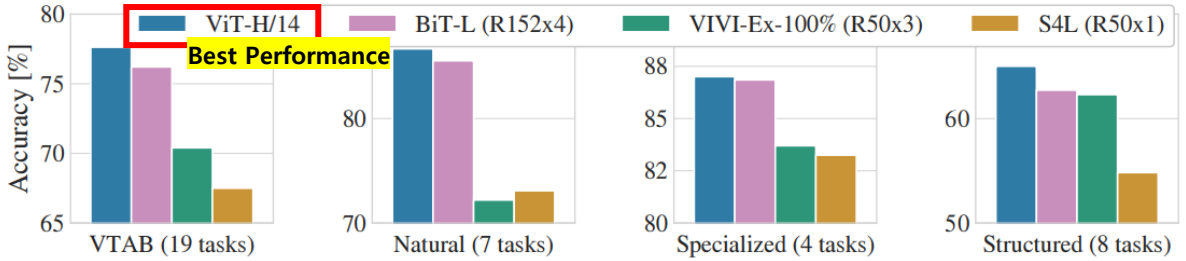
AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE (ICLR 2021)

- **Experiment:**
  - 전체적으로 다양한 benchmark dataset 에서 SOTA 달성.

Each Model size

Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

VTAB performance in Natural, Specialized, and Structured task groups



벤치마크된 lager 데이터셋으로 사전학습한 ViT와 SOTA 모델들의 데이터셋에 따른 성능 비교

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21k (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** ± 0.04	87.76 ± 0.03	85.30 ± 0.02	87.54 ± 0.02	88.4/88.5*
ImageNet ReaL	**90.72** ± 0.05	90.54 ± 0.03	88.62 ± 0.05	90.54	90.55
CIFAR-10	**99.50** ± 0.06	99.42 ± 0.03	99.15 ± 0.03	99.37 ± 0.06	–
CIFAR-100	**94.55** ± 0.04	93.90 ± 0.05	93.25 ± 0.05	93.51 ± 0.08	–
Oxford-IIIT Pets	**97.56** ± 0.03	97.32 ± 0.11	94.67 ± 0.15	96.62 ± 0.23	–
Oxford Flowers-102	99.68 ± 0.02	**99.74** ± 0.00	99.61 ± 0.02	99.63 ± 0.03	–
VTAB (19 tasks)	**77.63** ± 0.23	76.28 ± 0.46	72.72 ± 0.21	76.29 ± 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

한줄평: 개인적으로, 결국 많은 양의 데이터를 사용하지 않는 이상 좋은 성과를 볼 수 없고, 모델을 활용하는데 있어 Google research의 사전학습 데이터를 사용하는 것이 불가피하기 때문에 (Inductive bias 때문) **활용하기 힘든 단점**을 가진 것 같다.