

PATCHES ARE ALL YOU NEED?

Reading group

November 8th 2021

Convolutions Attention MLPs Patches Are All You Need?

Deep Learning Sessions Portugal

Anonymous authors

Paper under double-blind review

ABSTRACT

Although convolutional networks have been the dominant architecture for vision tasks for many years, recent experiments have shown that Transformer-based models, most notably the Vision Transformer (ViT), may exceed their performance in some settings. However, due to the quadratic runtime of the self-attention layers in Transformers, ViTs require the use of patch embeddings, which group together small regions of the image into single input features, in order to be applied to larger image sizes. This raises a question: Is the performance of ViTs due to the inherently-more-powerful Transformer architecture, or is it at least partly due to using patches as the input representation? In this paper, we present some evidence for the latter: specifically, we propose the ConvMixer, an extremely simple model that is similar in spirit to the ViT and the even-more-basic MLP-Mixer in that it operates directly on patches as input, separates the mixing of spatial and channel dimensions, and maintains equal size and resolution throughout the network. In contrast, however, the ConvMixer uses only standard convolutions to achieve the mixing steps. Despite its simplicity, we show that the ConvMixer outperforms the ViT, MLP-Mixer, and some of their variants for similar parameter counts and data set sizes, in addition to outperforming classical vision models such as the ResNet. Our code is available at https://github.com/tmp-iclr/convmixer.

TL;DR

- 4-page paper @ ICLR 2022;
- Propose ConvMixer Architecture = convolutions + patch embedding;
- Empirical validation using CIFAR-10 and ImageNet-1k
- Topics:
 - Vision Transformers (ViT), Patch Embeddings



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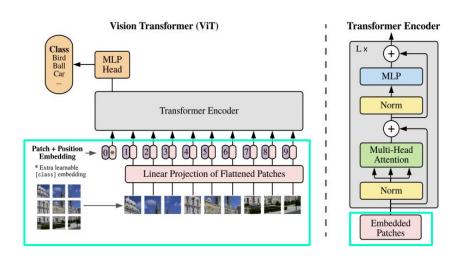
ABSTRACT

Although convolutional networks have been the dominant architecture for vision tasks for many years, recent experiments have shown that Transformer-based models, most notably the Vision Transformer (ViT), may exceed their performance in some settings. However, due to the quadratic runtime of the self-attention layers in Transformers, ViTs require the use of patch embeddings, which group together small regions of the image into single input features, in order to be applied to larger image sizes. This raises a question: Is the performance of ViTs due to the inherently-more-powerful Transformer architecture, or is it at least partly due to using patches as the input representation? In this paper, we present some evidence for the latter: specifically, we propose the ConvMixer, an extremely simple model that is similar in spirit to the ViT and the even-more-basic MLP-Mixer in that it operates directly on patches as input, separates the mixing of spatial and channel dimensions, and maintains equal size and resolution throughout the network. In contrast, however, the ConvMixer uses only standard convolutions to achieve the mixing steps. Despite its simplicity, we show that the ConvMixer outperforms the ViT, MLP-Mixer, and some of their variants for similar parameter counts and data set sizes, in addition to outperforming classical vision models such as the ResNet. Our code is available at https://github.com/tmp-iclr/convmixer.

RESEARCH QUESTION



Is the performance of ViTs due to the use of patches?

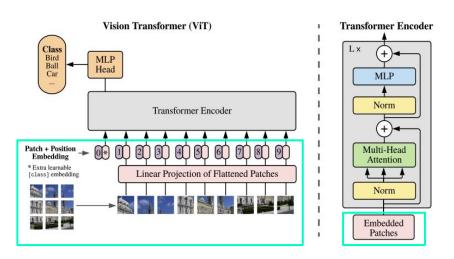


Source: An image is worth 16x16 words: Transformers for recognition at scale (ICLR 2021) - <u>Paper</u>, <u>ViT</u> Explained

RESEARCH QUESTION



Is the performance of ViTs due to the use of patches?



Note:

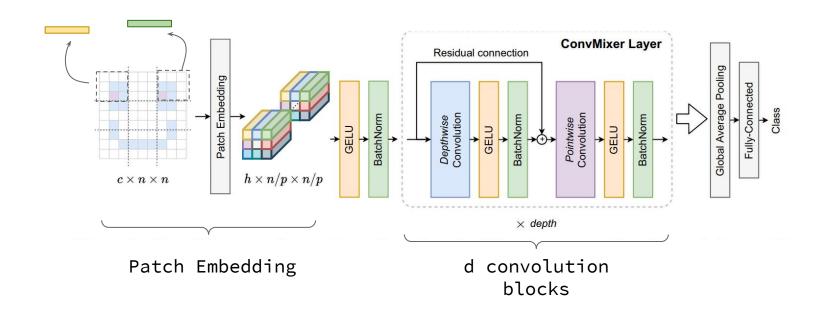
Interested in knowing more about patch-based vs full-convolution networks? Check this CVPR 2015 paper.

Source: An image is worth 16x16 words: Transformers for recognition at scale (ICLR 2021) - <u>Paper</u>, <u>ViT</u> Explained

CONVMIXER ARCHITECTURE



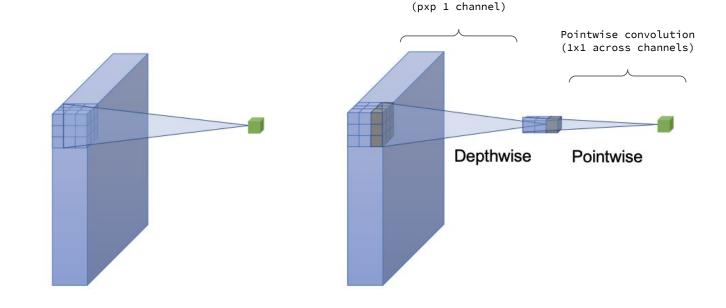
- Create patch embeddings;
- 2. Apply d depth-wise separable convolution blocks.



NOTE ON THE CONVOLUTION BLOCK

Standard Convolution





Depthwise convolution

Depth-wise separable convolution

Source: Image retrieved from <u>papers with code</u>, online accessed 8th November 2021. Also check <u>this blogpost</u> for more information on the differences.

DIFFERENCES TO MLP MIXER AND VIT



ConvMixer is similar to **MLP-Mixer**. MLP-Mixer separates mixing of spatial and channel dimensions, by applying an MLP across spatial dimension and then an MLP across the channel dimension (spatial MLP replaces the ViT attention and channel MLP is the FFN of ViT).

ConvMixer uses a 1x1 convolution for channel mixing and a depth-wise convolution for spatial mixing. Since it's a convolution instead of a full MLP across the space, it mixes only the nearby batches in contrast to ViT or MLP-Mixer. Also, the MLP-mixer uses MLPs of two layers for each mixing and ConvMixer uses a single layer for each mixing.

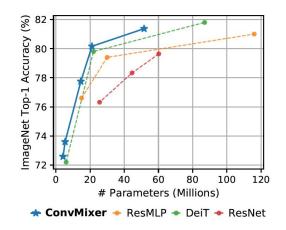
The paper recommends removing the residual connection across the channel mixing (point-wise convolution) and having only a residual connection over the spatial mixing (depth-wise convolution). They also use Batch normalization instead of Layer normalization.

Source: Summary retrieved from github, online accessed on the 8th November 2021.

RESULTS @ IMAGENET 1K







Current "Most Interesting" ConvMixer Configurations vs. Other Simple Models							
Network	Patch Size	Kernel Size	# Params (×10 ⁶)	Throughput (img/sec)	Act. Fn.	# Epochs	ImNet top-1 (%)
ConvMixer-1536/20	7 7	9	51.6	89	G	150	81.37
ConvMixer-768/32		7	21.1	203	R	300	80.16
ResNet-152	-	3 -	60.2	872	R	150	79.64
DeiT-B	16		86	703	G	300	81.8
ResMLP-B24/8	8		129	140	G	400	81.0

*ConvMixer-h/d represents the ConvMixer model trained with path embedding dimension h and d convolution blocks.

Trained using timm framework with several data augmentation strategies. (e.g., RandAugment, mixup, CutMix, random erasing, gradient norm clipping, timm augmentation)

GOOD PEER REVIEWER



GOOD PEER REVIEWER



- Simple, well written, straight to the point;
- Evaluate some of the best SotA models;
- Relevant research topic;

 Raises awareness to the importance of isolating the benefits of different components of complex architectures.

BAD PEER REVIEWER



BAD PEER REVIEWER



- Writing style may come across as rude;
- Main design decisions based on CIFAR-10;
- Questionable performance comparison:
 - Throughput is a concern -- Limited applicability in practice.
 - No Free Lunch Theorem (NFLT) -- No guarantees optimal training for ConvMixer is also optimal for ResNET or DeIT (more on this <u>this paper</u> and <u>this one</u>).
- Hyperparameter Optimization could be improved (why don't they use <u>Hyperband</u>?)





DEVELOPER



```
PyTorch Code:
```

https://github.com/tmp-iclr/convmixer

Is this <u>Ross Wightman</u>'s work?

Papers w/ code:

https://paperswithcode.com/paper/patches-are-all-you-need

LabAI.ml implementation:

https://nn.labml.ai/conv mixer/experiment.html

Torch2TF:

https://github.com/Rishit-dagli/ConvMixer-torch2tf









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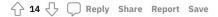
IntelArtiGen · 1m

Is the paper only interesting because of the new method and its simplicity? It's more parameter efficient (so is efficientnet) but the throughput is terrible





I think it's interesting as an ablation experiment - I don't think the goal of the paper is to say "this is a good new architecture that people should use", it's "the fact that this simple architecture works helps us narrow down what features of other models are most valuable".





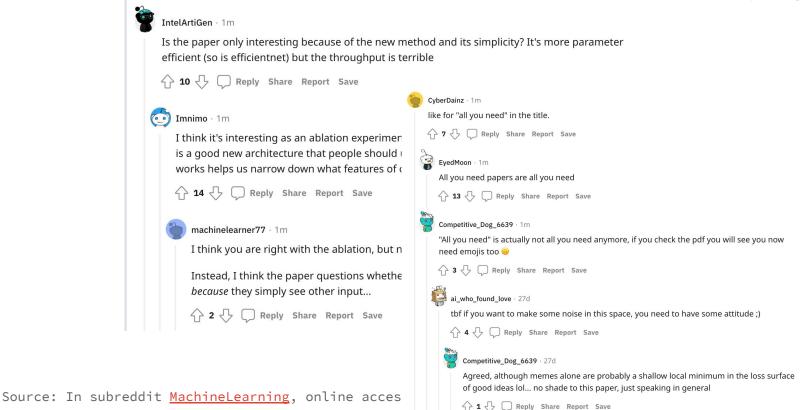
I think you are right with the ablation, but not fully correct with the rest.

Instead, I think the paper questions whether ViTs are so strong *because* they are ViTs or *because* they simply see other input...





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papers.labml.ai/papers/neurips...

Click on the papers to see videos, comments on social media, and related material.

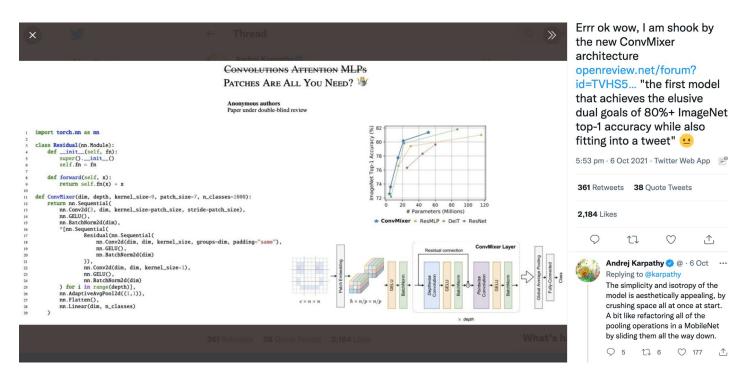


This trend of exploring MLPs and the connection between the strengths of ViT and convolutions dates back to (at least) NeuRTPS 2021...

Source: In Twitter labml.ai, online accessed 8 November 2021.



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JOURNALIST **TOTAL**







Dmitry @RespectToX · 6 Oct ... Replying to @karpathy Resnets: downsampling is effective, but adds noise and breaks shift equivariance. So, get rid of downsampling, except the first layer (where it is least harmful). Cool, but it is 10x slower than resnet. Next step is 100% strideless model, magnitudes slower, but even simpler 03



xhlulu @xhluu · 6 Oct Replying to @karpathy

I'm curious how much of the improvement is in the architecture vs the improved training tools thanks to timm, considering Resnet-50 can achieve 80%+ without any architecture change: arxiv.org/pdf/2110.00476...

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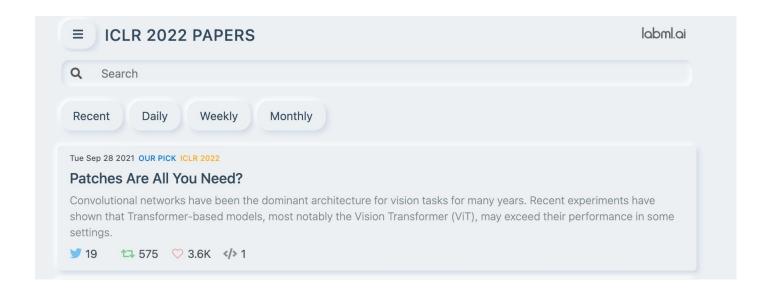


There are so many tweets... Here are some examples:

Horace He @ Facebook (cHHillee)







Source: In labml.ai selection of ICLR 2022 papers, online accessed 8 November 2021.





ARCHEOLOGIST



Background:

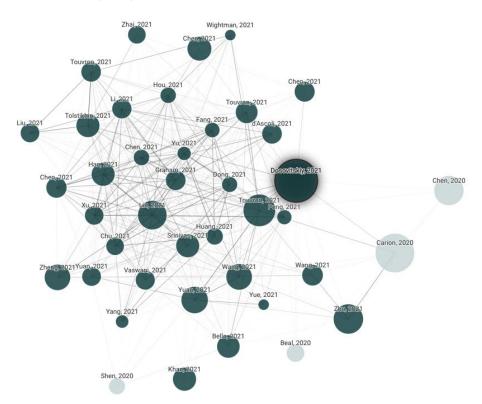
Attention is all you need (2017) - Intro to Transformers

Image is worth 16x16 words (2021) - Intro to ViTs

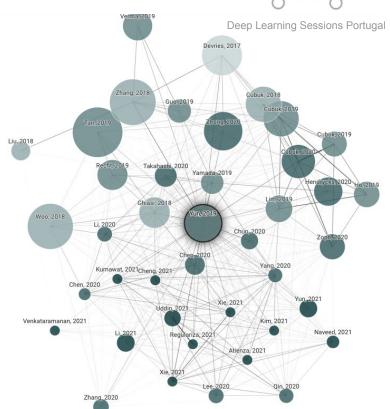
- 2019 and 2020 references: Attention + Convolution, or training strategies;
- 2021 references focused on deconstructing ViT, e.g., MLP-Mixer, ResMLP, PVT, CycleMLP, SwinTransformer, etc.

ARCHEOLOGIST





ViT (@ICLR 2021) similarity graph @ ConnectedPapers.



CutMix (@CVPR 2019) similarity graph @ ConnectedPapers.





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Please share with us <u>your opinion</u> on papers you'd love to discuss in upcoming sessions!