Astroformer: More Data Might not be all you need for Classification

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Data is at the heart of modern AI

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- Dataset Sizes for Image Classification:
    - MNIST - 60K
    - CIFAR 10,100 - 60K
    - Fashion-MNIST - 70K
    - ImageNet - 14M
    - JFT - 300M
    - JFT - 3B

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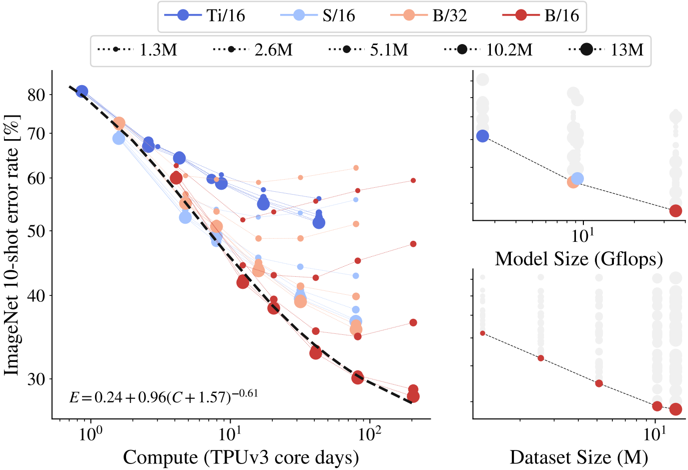
- Rise of Transformers and Vision Transformers, well known since Bahdanau attention [Bahdanau et al.,2014] that Attention-based models scale very well with the amount of training data

Data is at the heart of modern AI



Scaling Vision Transformers, Zhai et al., 2022

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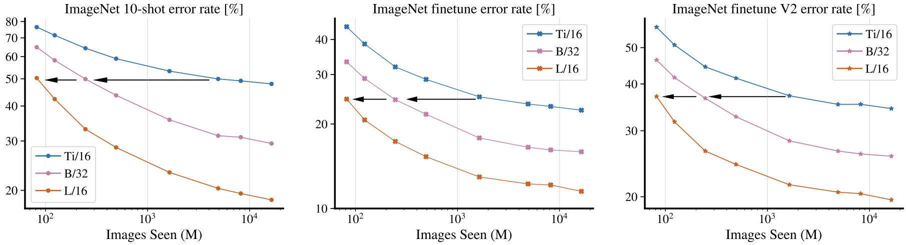

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Model	top-1 accuracy (↑)
Efficient Adaptive Ensembling	99.612
ResNet56	74.44
ResNet110	76.18
EfficientNet B0	61.64
ResNet18	64.49
ViT (scratch)	73.81
ViT-Drloc	58.29
SL-ViT	76.92

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- Vision Transformers (monolithic or non-monolithic) suffer heavily when trained from scratch on small datasets
- Inherent inductive biases allow training CNNs on small-scale datasets from scratch [D'Ascoli et al., 2021]
- Vision Transformers often have a lack of locality, inductive biases, and hierarchical structure of the representations

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How to Train your ViT?

- ViTs require large-scale pre-training to learn the properties they lack from large-scale data
- All SOTA Vision transformers: BASIC-L, CoCa, CoAtNet, and ViT-G are trained on JFT datasets
- Transformers are often pre-trained and then fine-tuned for acceptable performance

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Intuitively Merging Convolutions and Attention

Multiple attempts in the past.

$$A_{i,j} = \sum_{k \in \mathcal{G}} \exp\left(x_i^\top x_k\right) \quad \text{(standard self-attention)}$$

$$A_{i,j} = \sum_{k \in \mathcal{G}} \exp\left(x_i^\top x_k + w_{i-k}\right)$$

x_i, $y_i \in \mathbb{R}^d$ are the input and output at position i, w_{i-j} represents the depthwise convolution kernel and $\mathcal{G}$ represents the global spatial space

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$$y_i = \sum_{j \in \mathcal{G}} \frac{\exp\left(x_i^\top x_j + w_{i-j}\right)}{\sum_{k \in \mathcal{G}} \exp\left(x_i^\top x_k + w_{i-k}\right)} x_j$$

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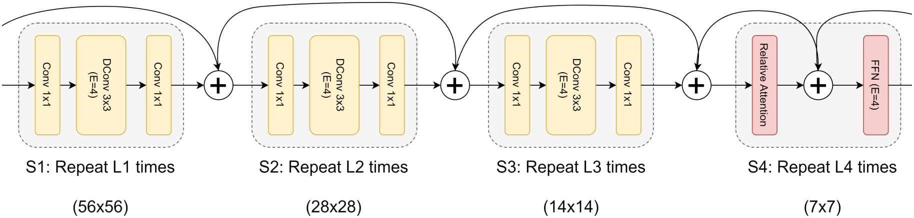
Model



- Core includes C-C-C-T which has been earlier thought to not work well [Dai et al., 2021; Tu et al., 2022]
- Comes with theoretical improvements
- Multiple other components

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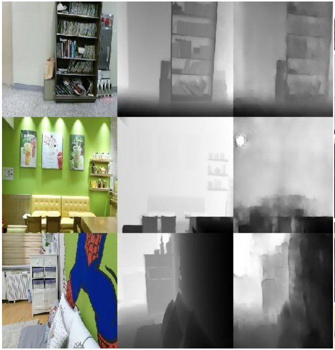
Results

- We set a new SOTA on Tiny ImageNet (by 0.98%)
- We set a new SOTA on CIFAR-100 w/o extra training data (by 3.46%)
- We set a new SOTA on Galaxy10 DECals (by 4.62%)
- Competitive performance on CIFAR-10 (99.12%)

As a backbone



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Thank You