How Do Vision Transformers Work?

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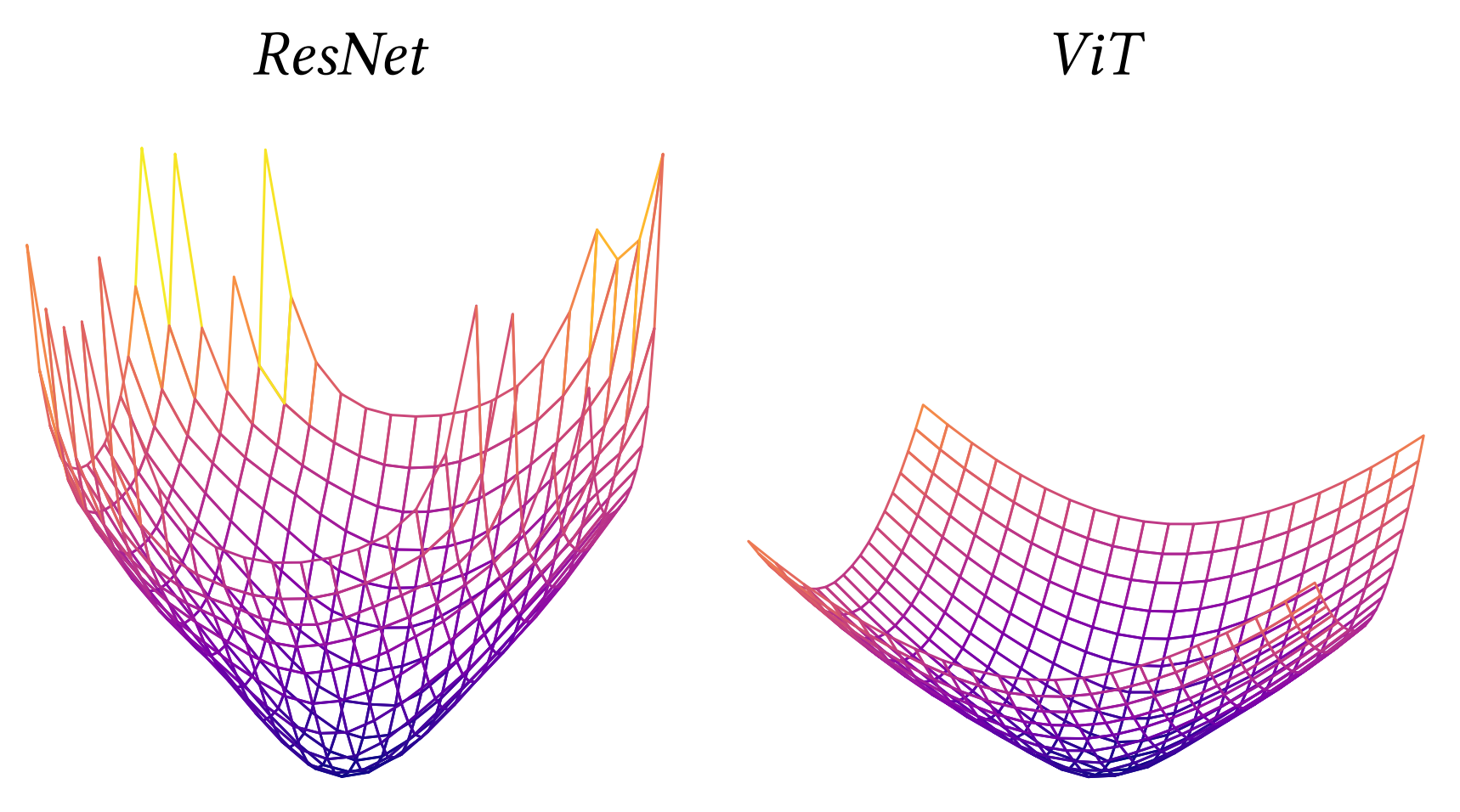
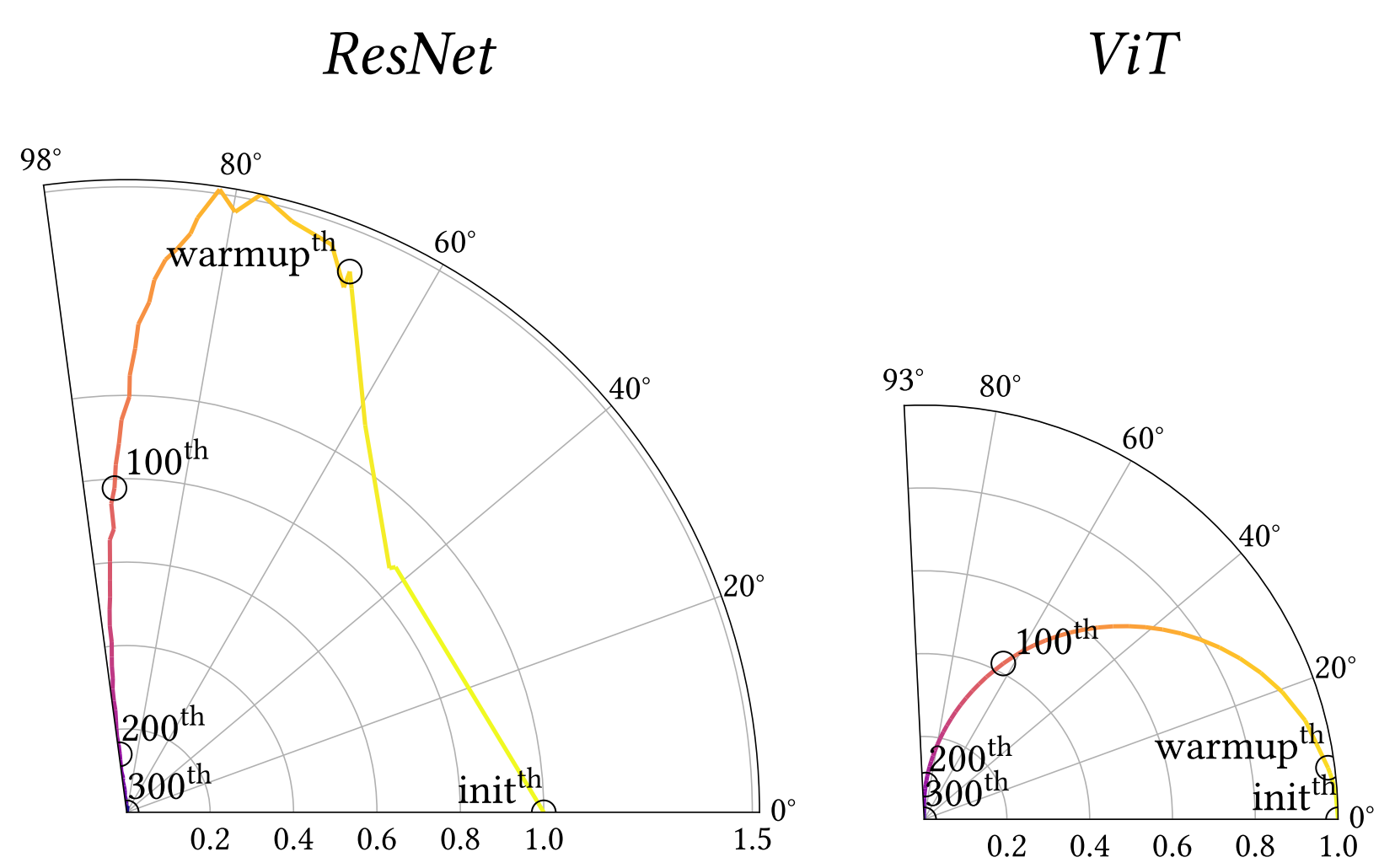
Paper: https://arxiv.org/abs/2202.06709
Code: https://github.com/xxxnell/how-do-vits-work

What Properties of Self-Attentions Do We Need?

MSAs (multi-head self-attention) have flat but non-convex losses. In contrast, Convs have convex but sharp losses.

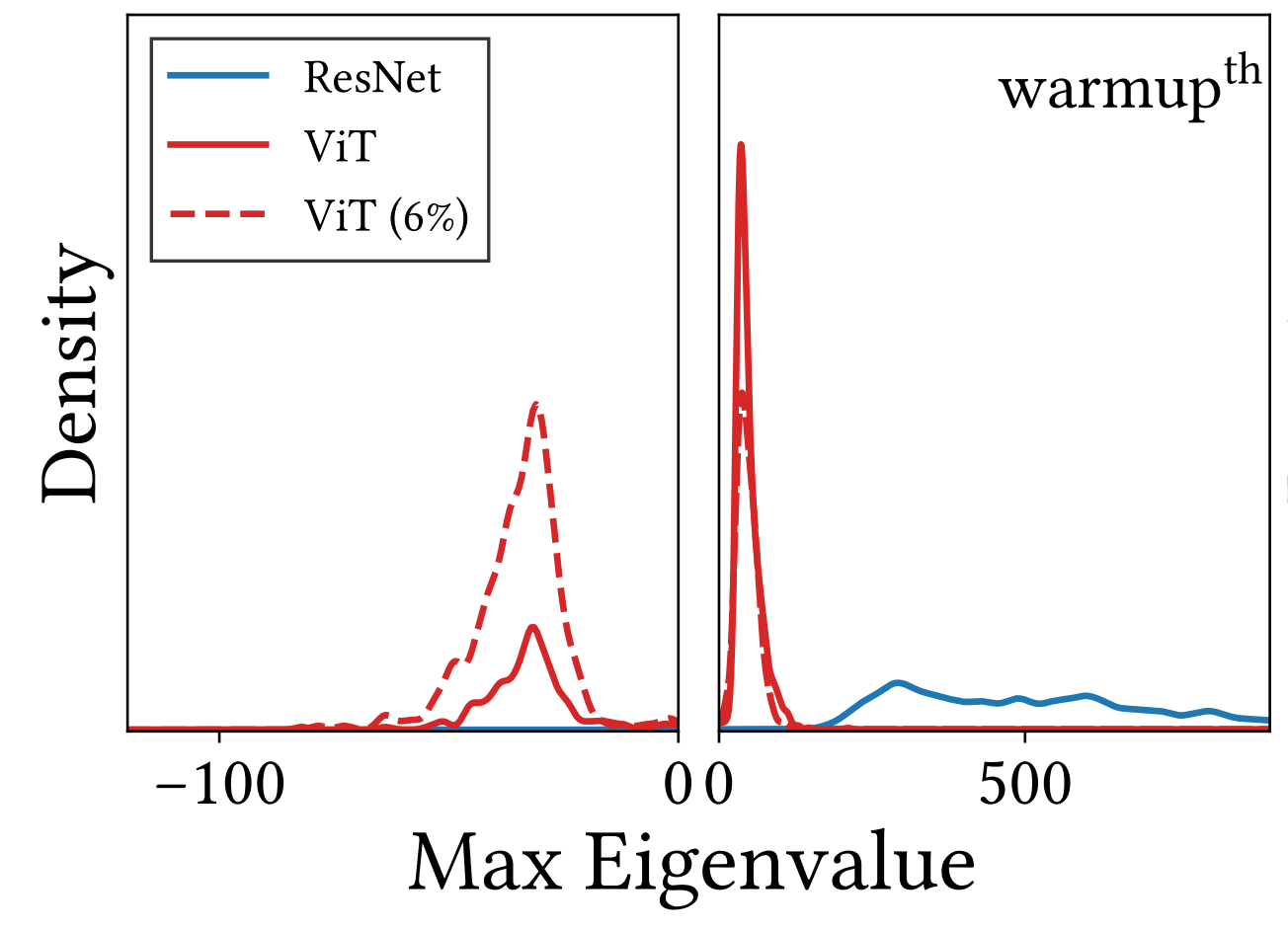


(a) Loss landscape visualization

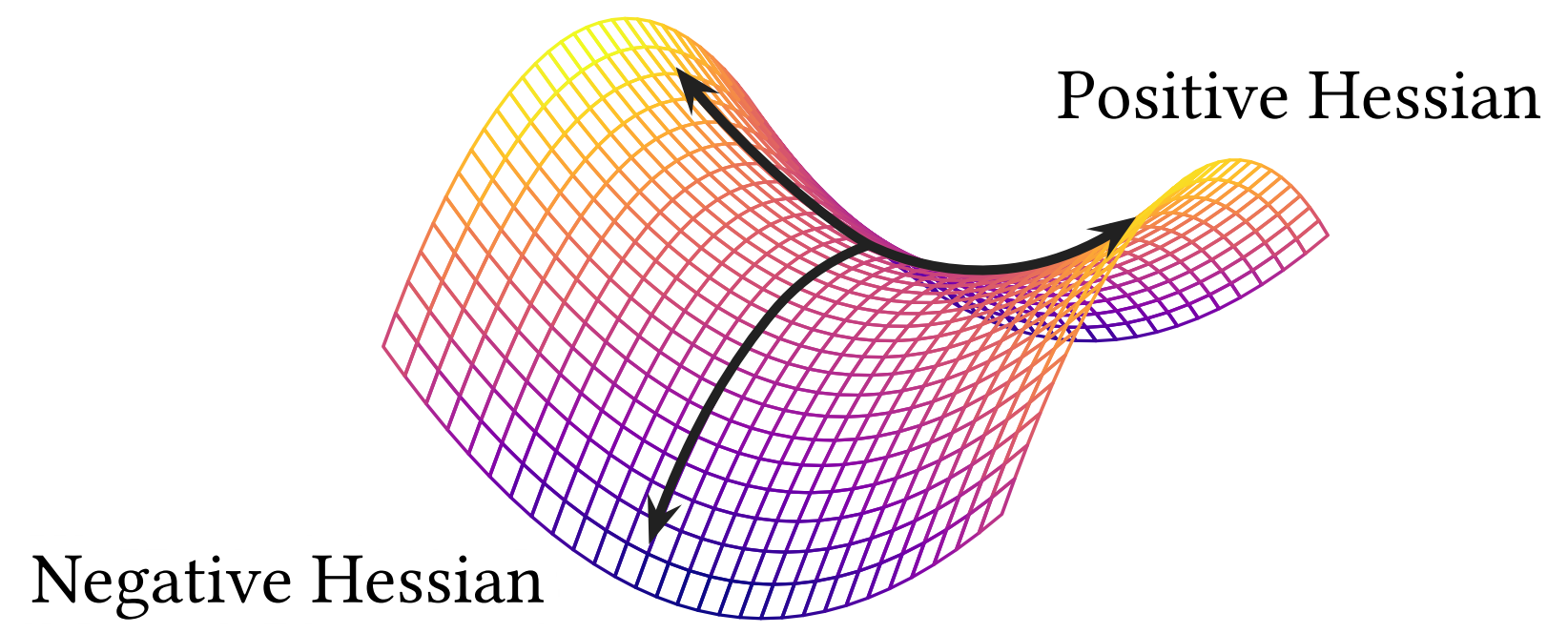


(b) Learning trajectory in polar coordinate

Loss landscape visualization (*Left*) show that ViT has a flatter loss than ResNet. **Learning trajectory visualization (*Right*)** shows that ViT converges to the optimum along a smooth trajectory.

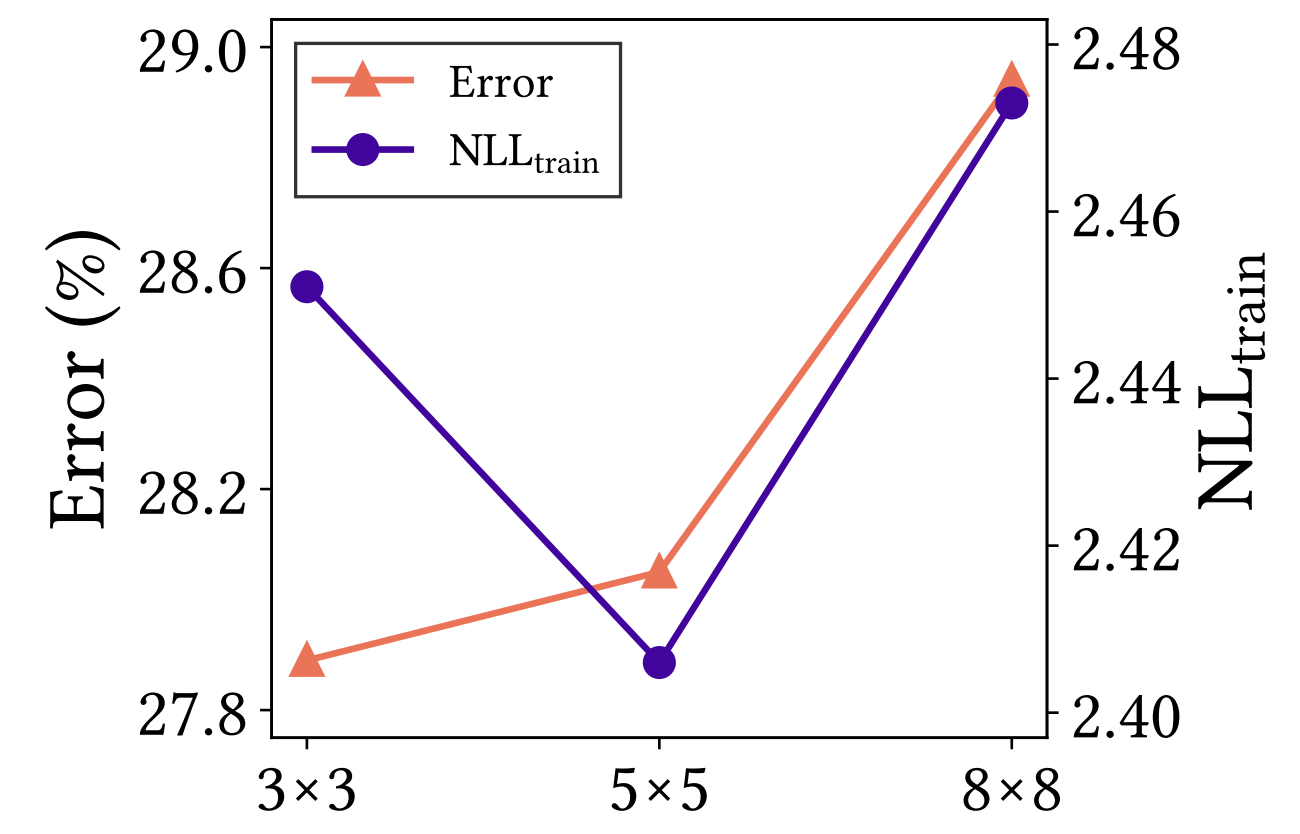


(a) Hessian eigenvalue spectrum

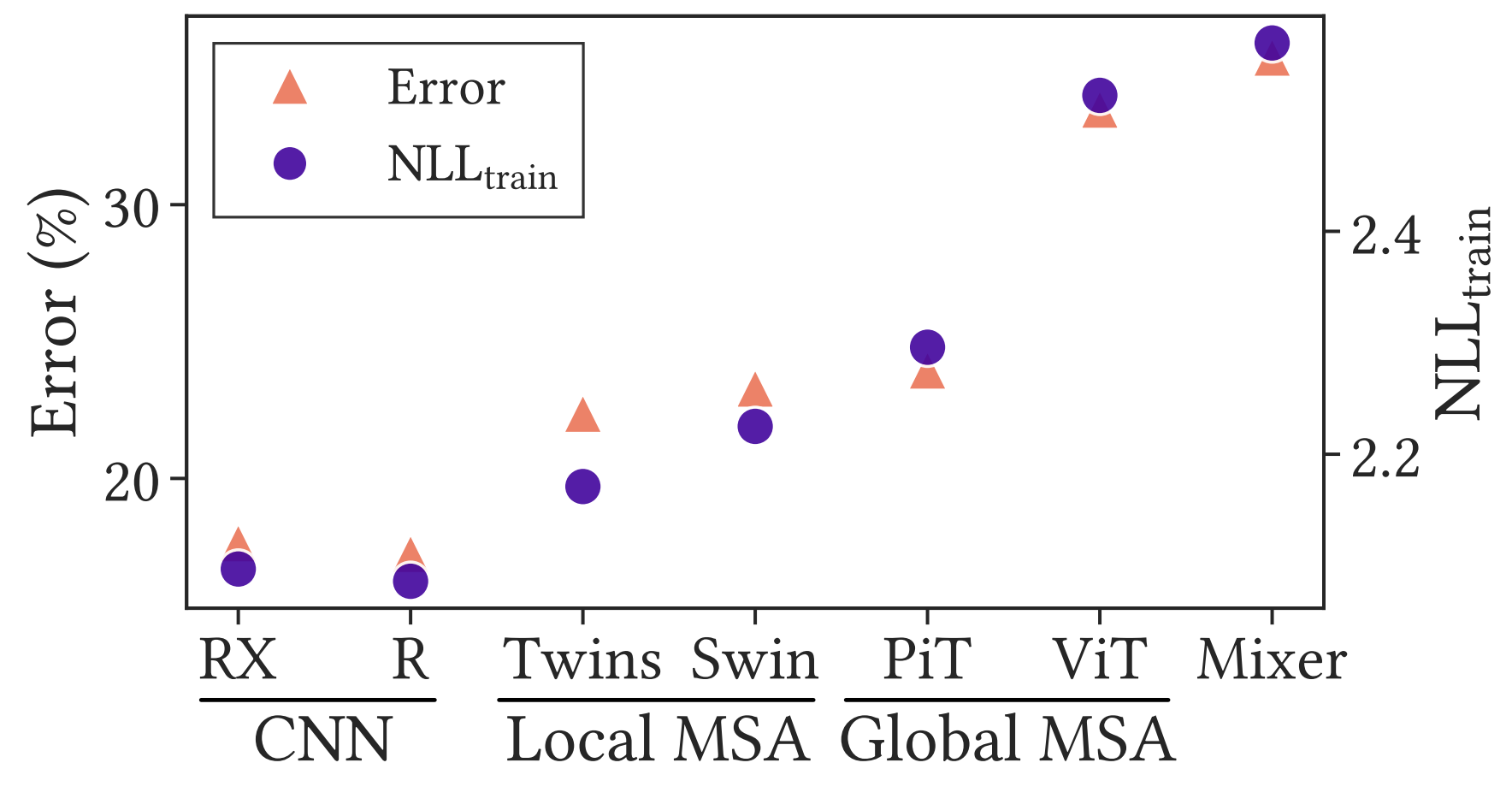


(b) Local geometry of non-convex (saddle) points

Hessian max eigenvalue spectra show that MSAs have their pros and cons. ViT has a number of negative Hessian eigenvalues, while ResNet only has a few. The magnitude of ViT's positive Hessian eigenvalues is small.



(a) Error and NLL of ViT with local MSA for kernel size

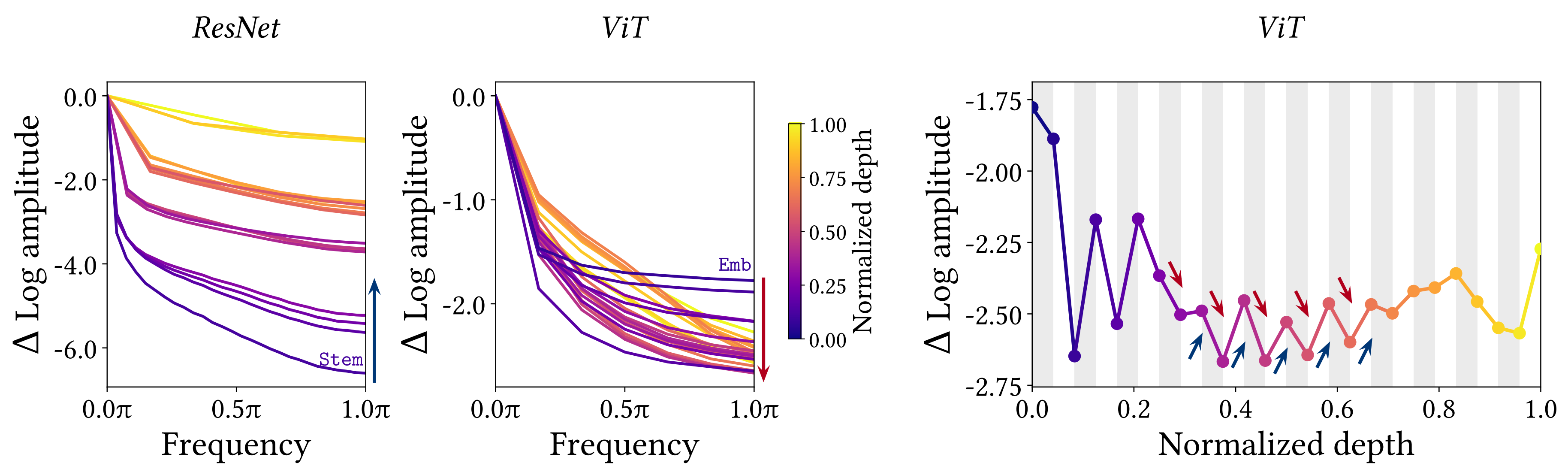


(b) Test error and training NLL for each model

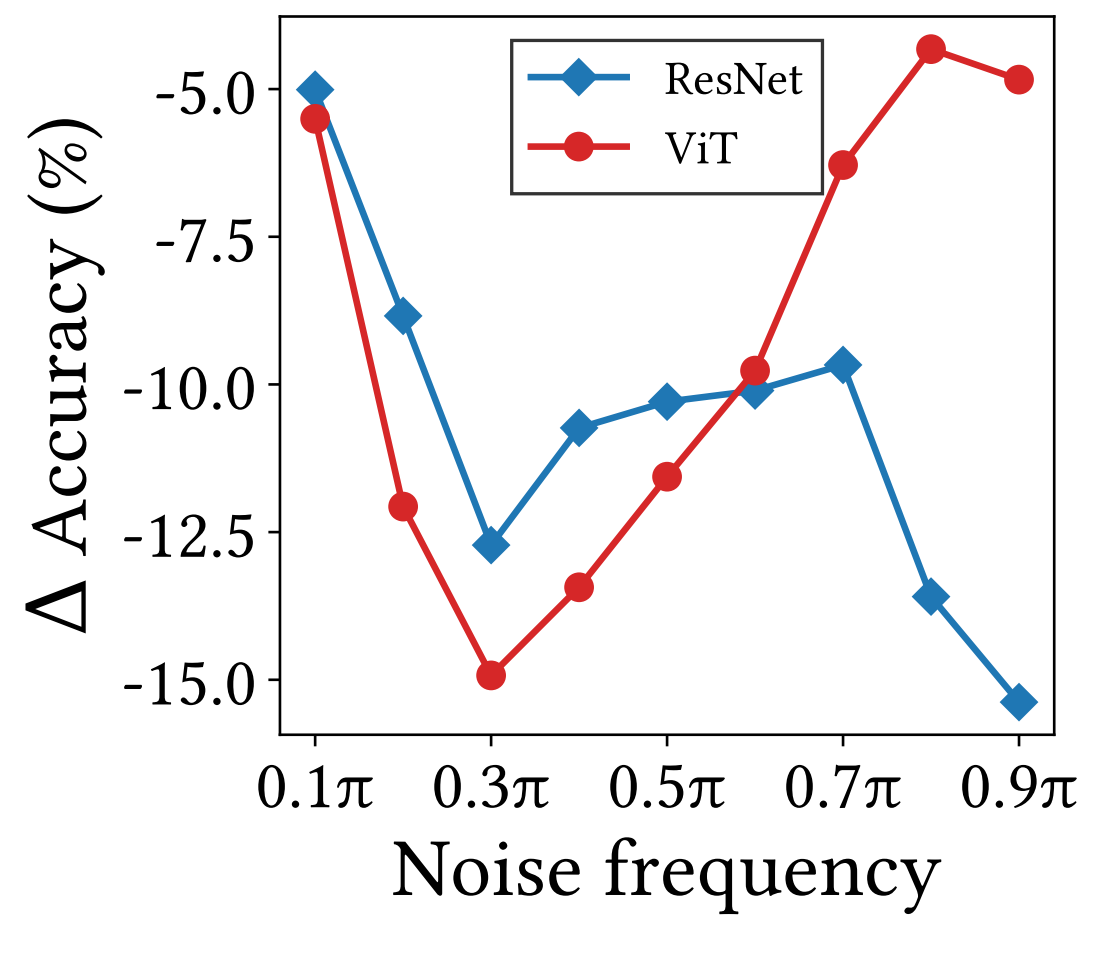
The key feature of MSA is data specificity, not long-range dependency. *Left*: Convolutional ViT demonstrates that locality constraint improves ViT. *Right*: Weak inductive bias (e.g. long-range dependency) disturbs NN optimization.

Do Self-Attentions Act Like Convs?

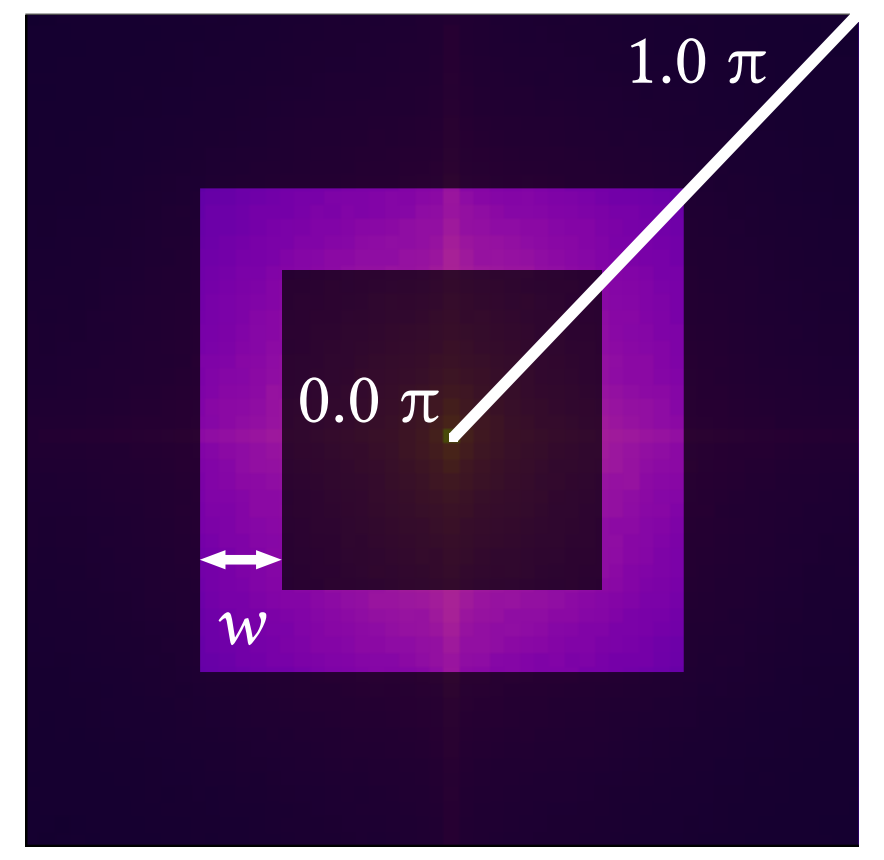
MSAs are low-pass filter, but Convs are high-pass filter. It suggests that MSAs are shape-biased, whereas Convs are texture-biased.



Relative log amplitudes of **Fourier transformed feature map** show that ViT tend to reduces high-frequency signals, while ResNet amplify them. ***Left***: In ViT, MSAs (gray area) generally reduce the high-frequency (1.0π) component of feature map, and Conv/MLPs (white area) amplify it.



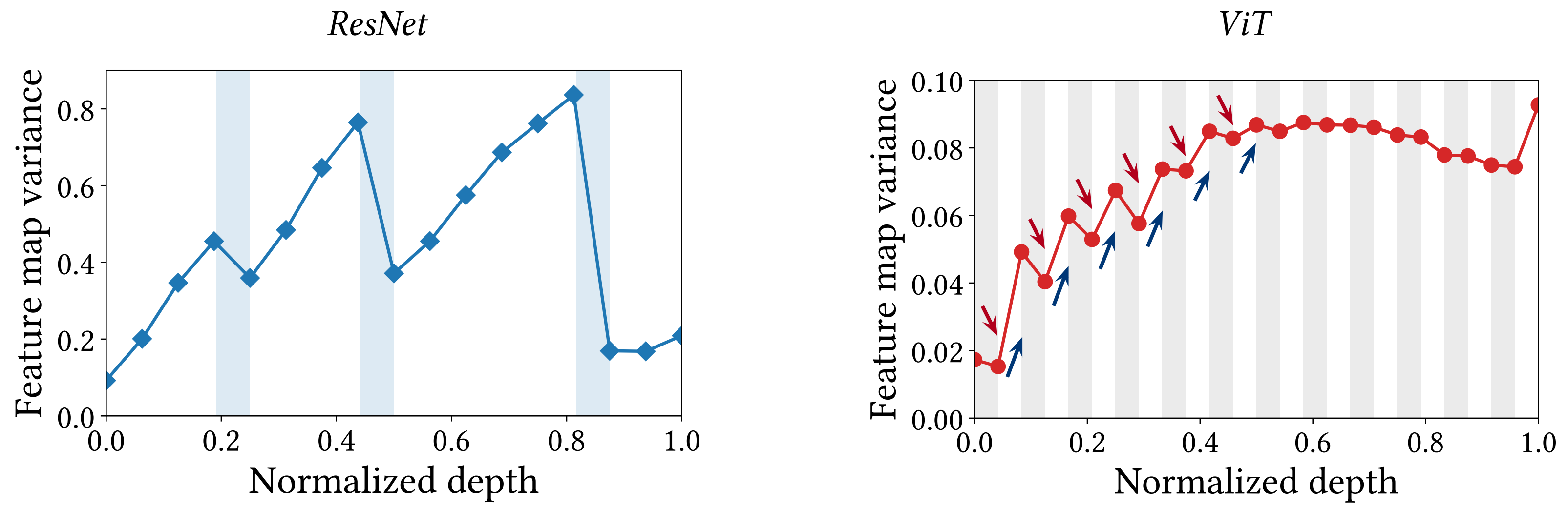
(a) Robustness for noise frequency



(b) Frequency-based random noise

We measure the **decrease in accuracy against frequency-based random noise**. ViT is robust against high-frequency noise, while ResNet is vulnerable to them.

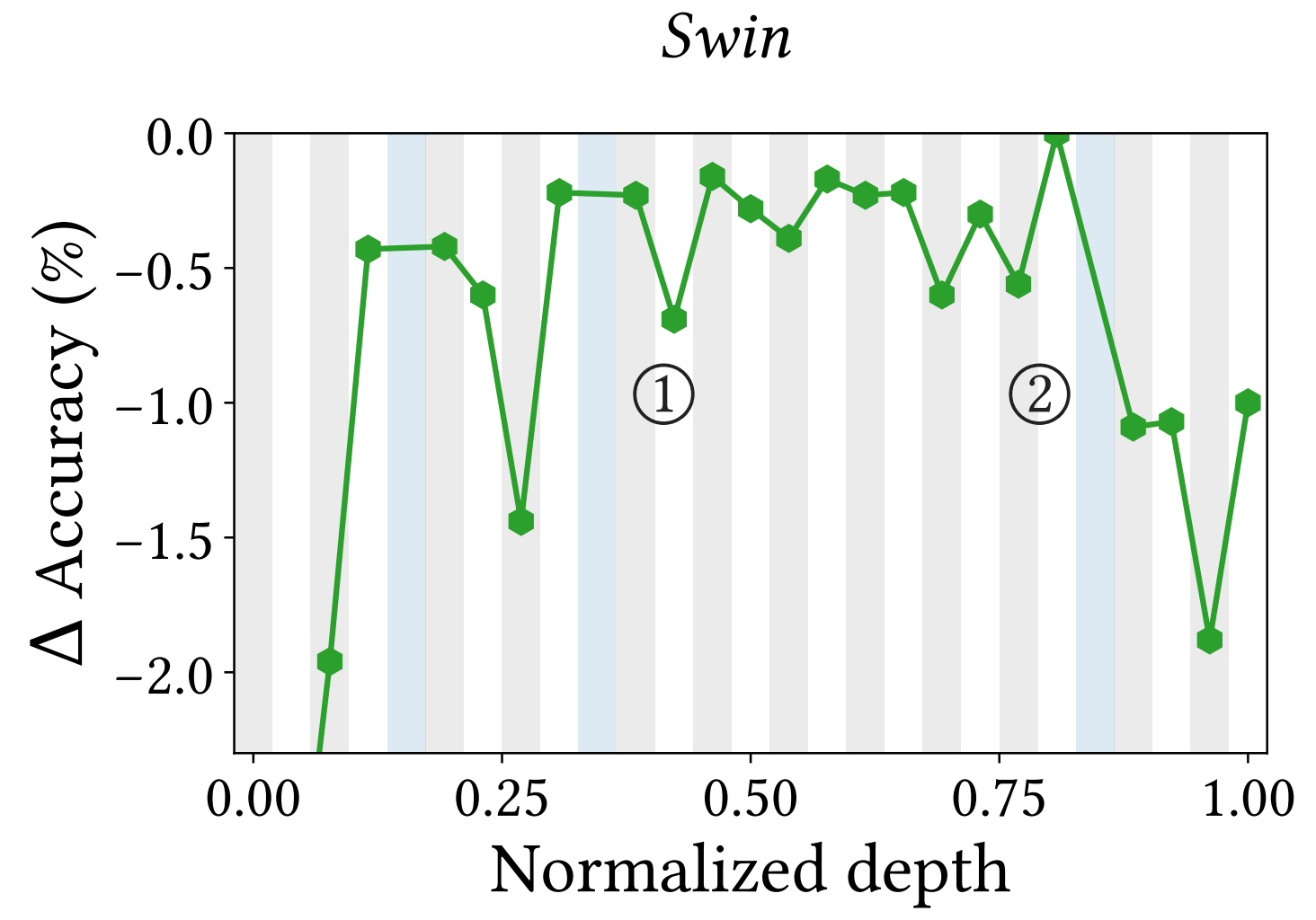
It suggests that low-frequency signals and high-frequency signals are informative to MSAs and Convs.



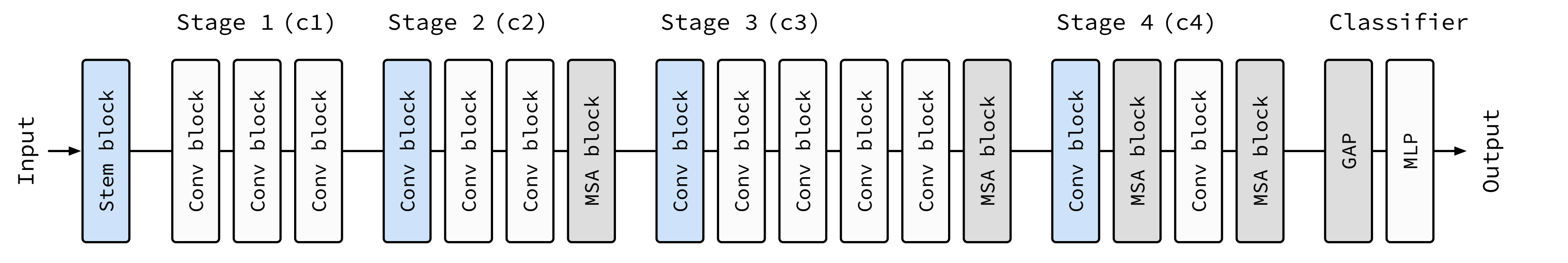
MSAs (gray area) reduce **the variance of feature map points**, but Convs/MLPs (white area) increase the variance. The blue area is subsampling layer. The results implies that MSAs aggregate feature maps, and Convs convert them.

How Can We Harmonize Self-Attentions with Convs?

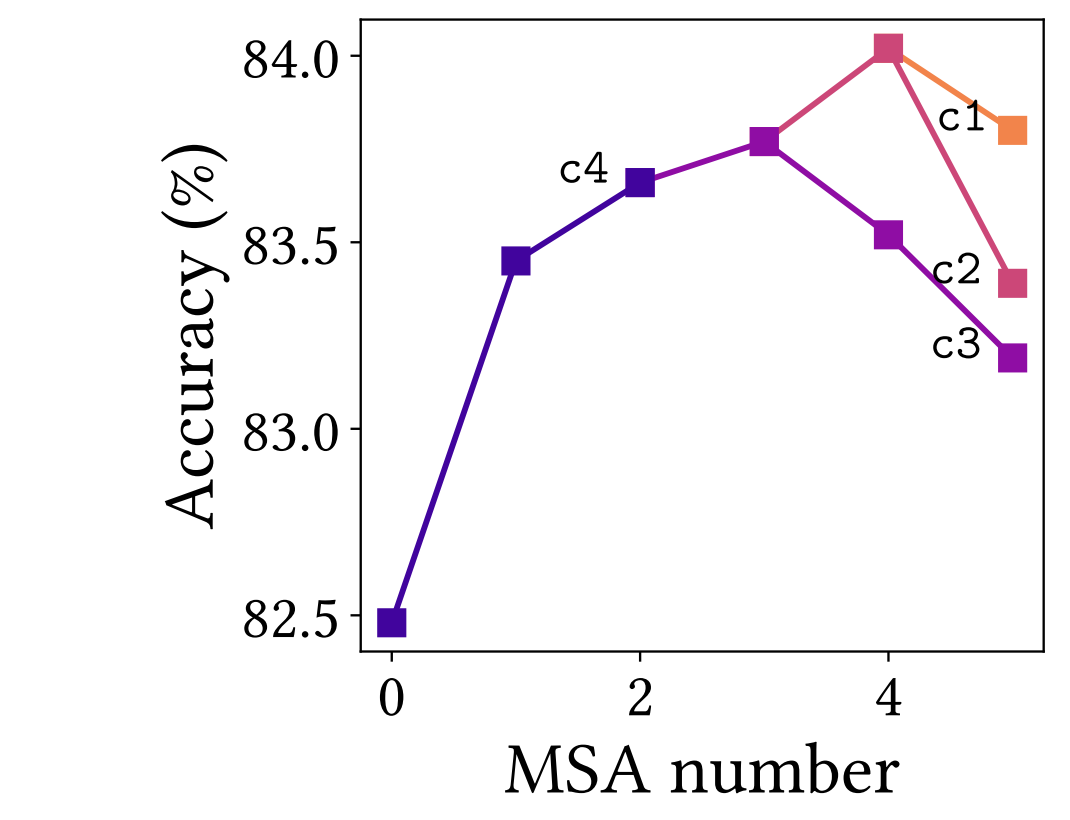
MSAs closer to the end of a stage (not a model) and Convs at the beginning of a stage significantly improve the performance.



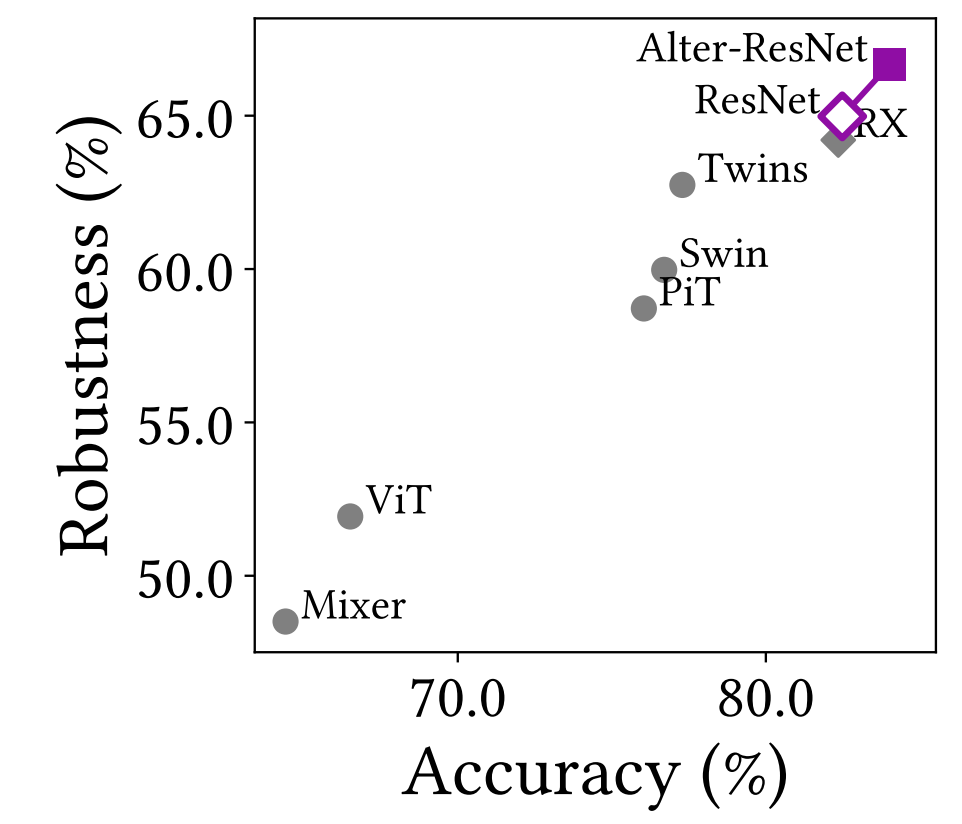
We measure **decrease in accuracy after removing one unit** from the trained model. Accuracy changes periodically, and this period is one stage. In Swin, ① Convs (white area) play an important role at the beginning of a stage, and ② MSAs (gray area) play an important role at the end of a stage.



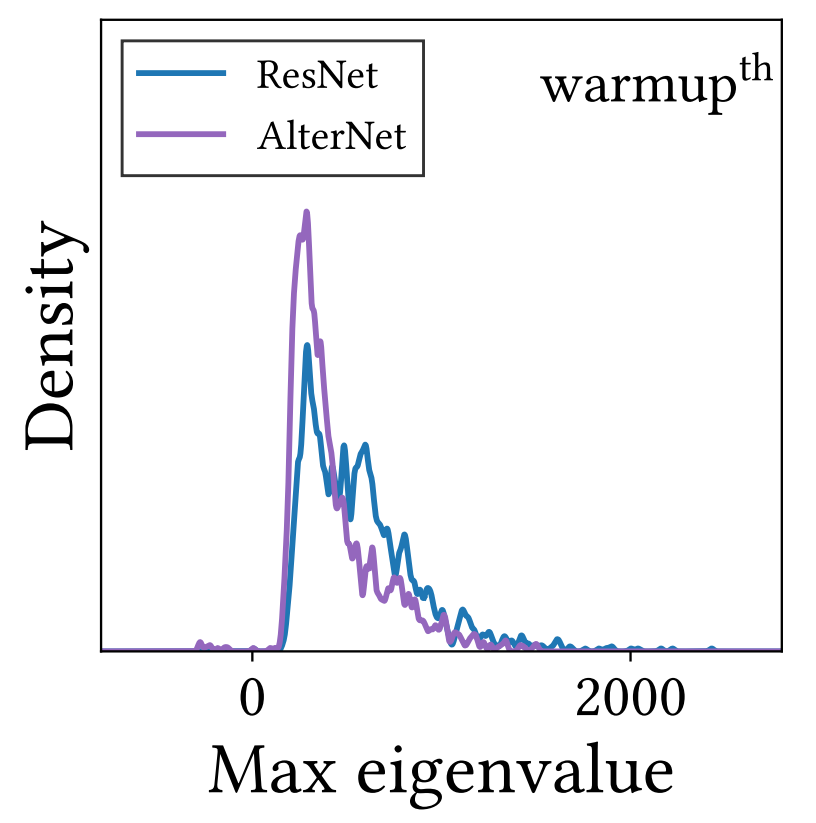
(a) Architecture of Alter-ResNet-50 for CIFAR-100



(b) Accuracy of AlterNet for MSA number



(c) Accuracy and robustness in a small data regime (CIFAR-100)



(d) Hessian max eigenvalue spectra

We propose ***AlterNet***, a model in which Conv blocks at the end of *a stage* are replaced with MSA blocks. AlterNet outperforms CNNs even in small data regimes.

In summary, appropriate inductive biases improves NN optimization, and self-attentions have a spatial smoothing inductive bias.

	Self-Attention	Convolution
Loss Landscape	Flat but non-convex	Convex but sharp
Fourier Analysis	Low-pass filter (shape-biased)	High-pass filter (texture-biased)
Best Practice	The end of a stage	The beginning of a stage