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# A Modern Look at the Relationship between Sharpness and Generalization

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# Contributions

Can sharpness predict generalization in modern practical settings?

- Empirical evaluation:
  1. training from scratch on {ImageNet, CIFAR-10} with {transformers, CNNs}
  2. fine-tuning transformers on ImageNet and MNLI
- Observation:
  1. sharpness does not correlate well with generalization
  2. sharpness correlates well with LR
- In some cases, sharper minima can generalize better
- Analysis on toy model:
  1. right sharpness measure for generalization is highly data-dependent

Background

# Sharpness definitions

- Adaptive average-case m-sharpness wrt vector  $\mathbf{c}$  in  $\mathbb{R}^p$ :

$$S_{avg}^\rho(\mathbf{w}, \mathbf{c}) \triangleq \mathbb{E}_{\substack{\mathcal{S} \sim P_m \\ \boldsymbol{\delta} \sim \mathcal{N}(0, \rho^2 \text{diag}(\mathbf{c}^2))}} L_{\mathcal{S}}(\mathbf{w} + \boldsymbol{\delta}) - L_{\mathcal{S}}(\mathbf{w}),$$

- Adaptive worst-case m-sharpness wrt vector  $\mathbf{c}$  in  $\mathbb{R}^p$  for radius  $\rho$ :

$$S_{max}^\rho(\mathbf{w}, \mathbf{c}) \triangleq \mathbb{E}_{\mathcal{S} \sim P_m} \max_{\|\boldsymbol{\delta} \odot \mathbf{c}^{-1}\|_p \leq \rho} L_{\mathcal{S}}(\mathbf{w} + \boldsymbol{\delta}) - L_{\mathcal{S}}(\mathbf{w}),$$

- Experiments use  $L_\infty$  worst-case adaptive sharpness with  $m=256$

# Is sharpness predictive of generalization?

- Strong hypothesis:
  - low sharpness  $\Leftrightarrow$  high generalization (high correlation)
  - causal relation
- Weak hypothesis:
  - low sharpness  $\Rightarrow$  high generalization
  - sufficient but not necessary
- Spoiler: neither hypotheses hold empirically

# When can we compare sharpness across models?

- Only compare models within **the same loss surface**
- For the same loss surface:
  1. architecture should be the same
  2. set of points to measure sharpness should be the same

# Invariances for sharpness

- If  $T(w)$  does not change predictions, then it should not change sharpness
- Adaptive sharpness has such invariances
- Need to normalize classification logits to get scale-invariance:

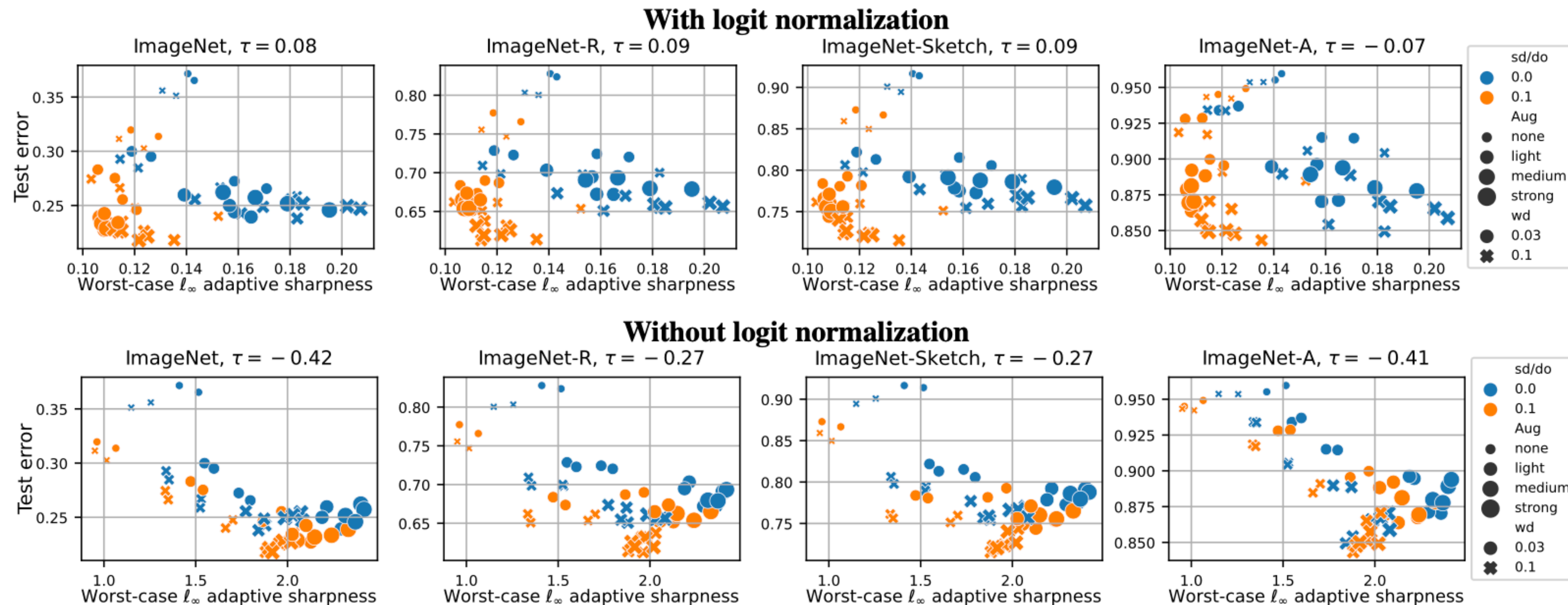
$$\tilde{f}_{\mathbf{w}}(\mathbf{x}) \triangleq \frac{f_{\mathbf{w}}(\mathbf{x})}{\sqrt{\frac{1}{K} \sum_{i=1}^K (f_{\mathbf{w}}(\mathbf{x})_i - f_{avg}(\mathbf{x}))^2}},$$

# Experiments



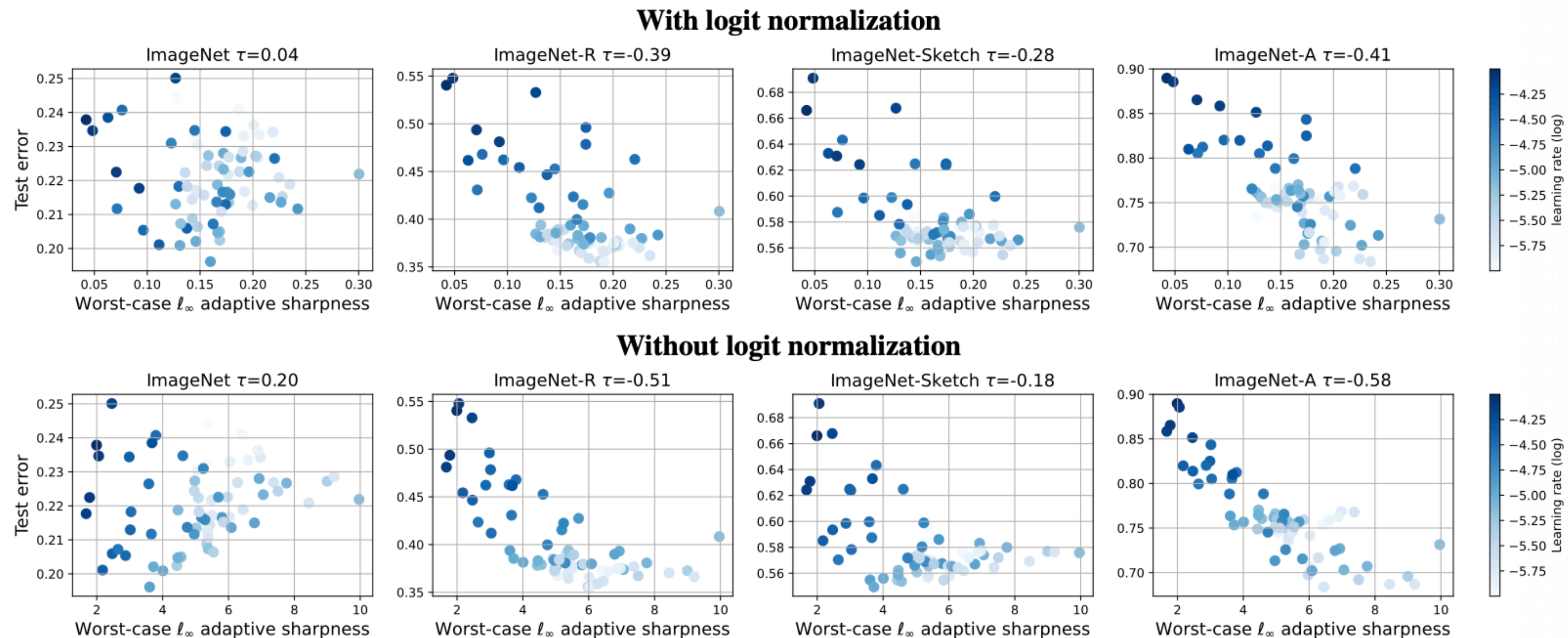
# Setting 1: ImageNet training from scratch

- 56 ViT models w different hparams: augmentations, weight decay, dropout, etc
- Test errors from 21.8% to 37.2%



# Setting 2: Fine-tuning on ImageNet-1k from CLIP

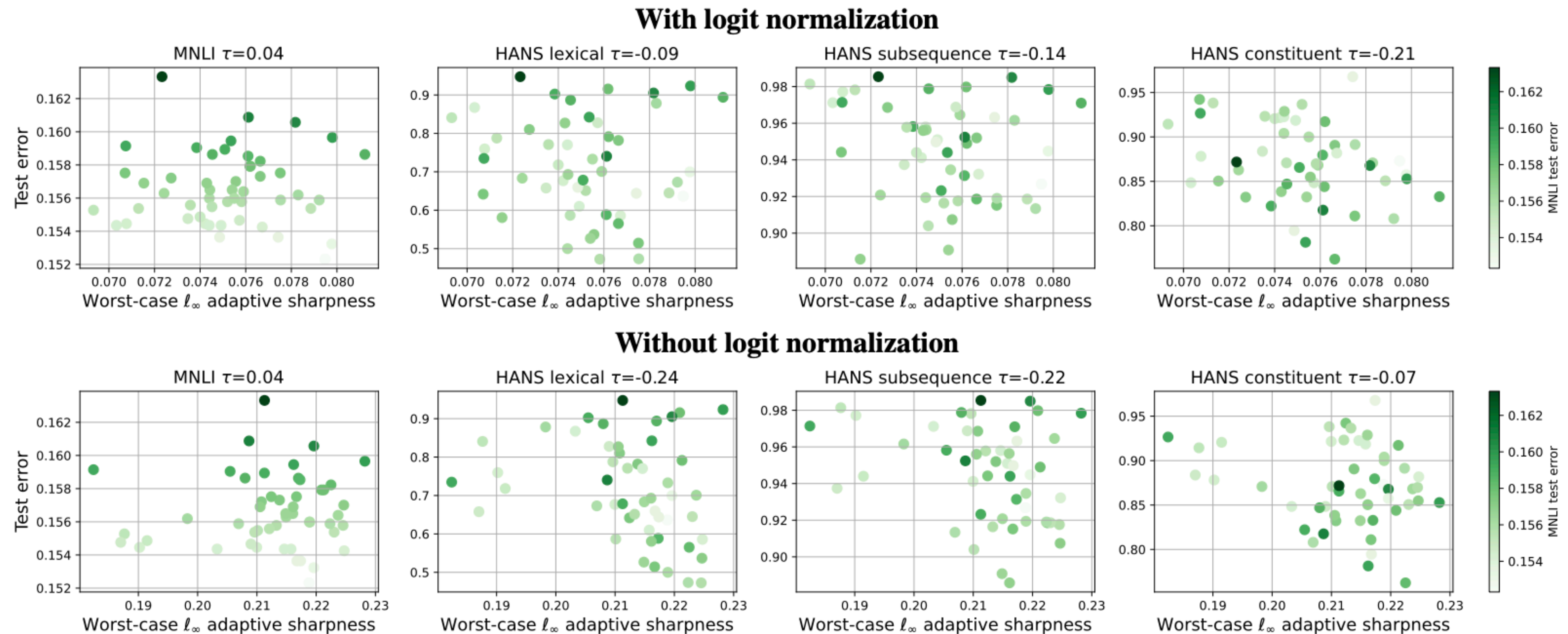
- 71 fine-tuned CLIP ViT models w hparams: LR, epochs, wt decay, label smoothing, data aug
- Note: higher LR => higher test error. Flatter minima are worse on OOD.





# Setting 3: Fine-tuning BERT on MNLI

- 50 fine-tuned BERT models w different seeds: random clf head init, random batching



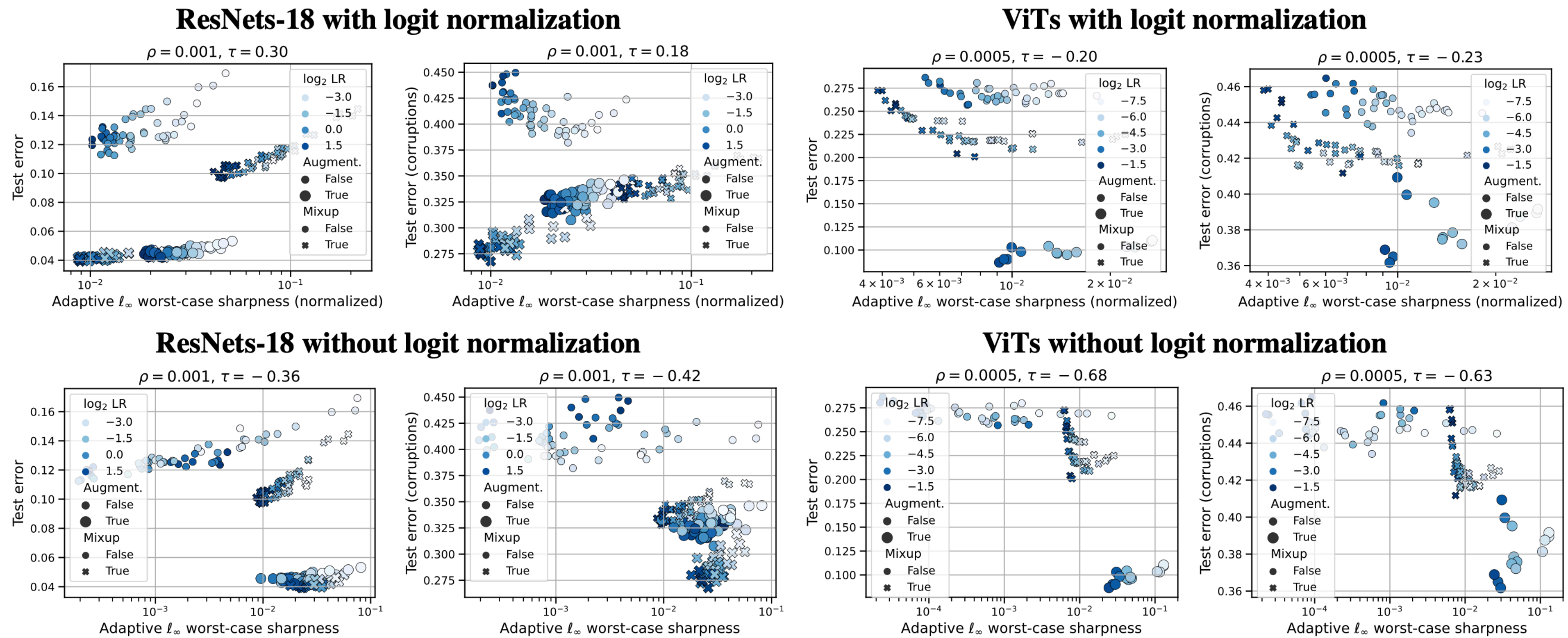
Analysis

# Why are these results counter to prior work?

- Architecture? transformers vs CNNs
- Larger datasets? ImageNet vs CIFAR-10
- Measure sharpness close to a minimum
- New controlled setup: ResNet vs ViTs, on CIFAR-10, trained to ~0% train error.

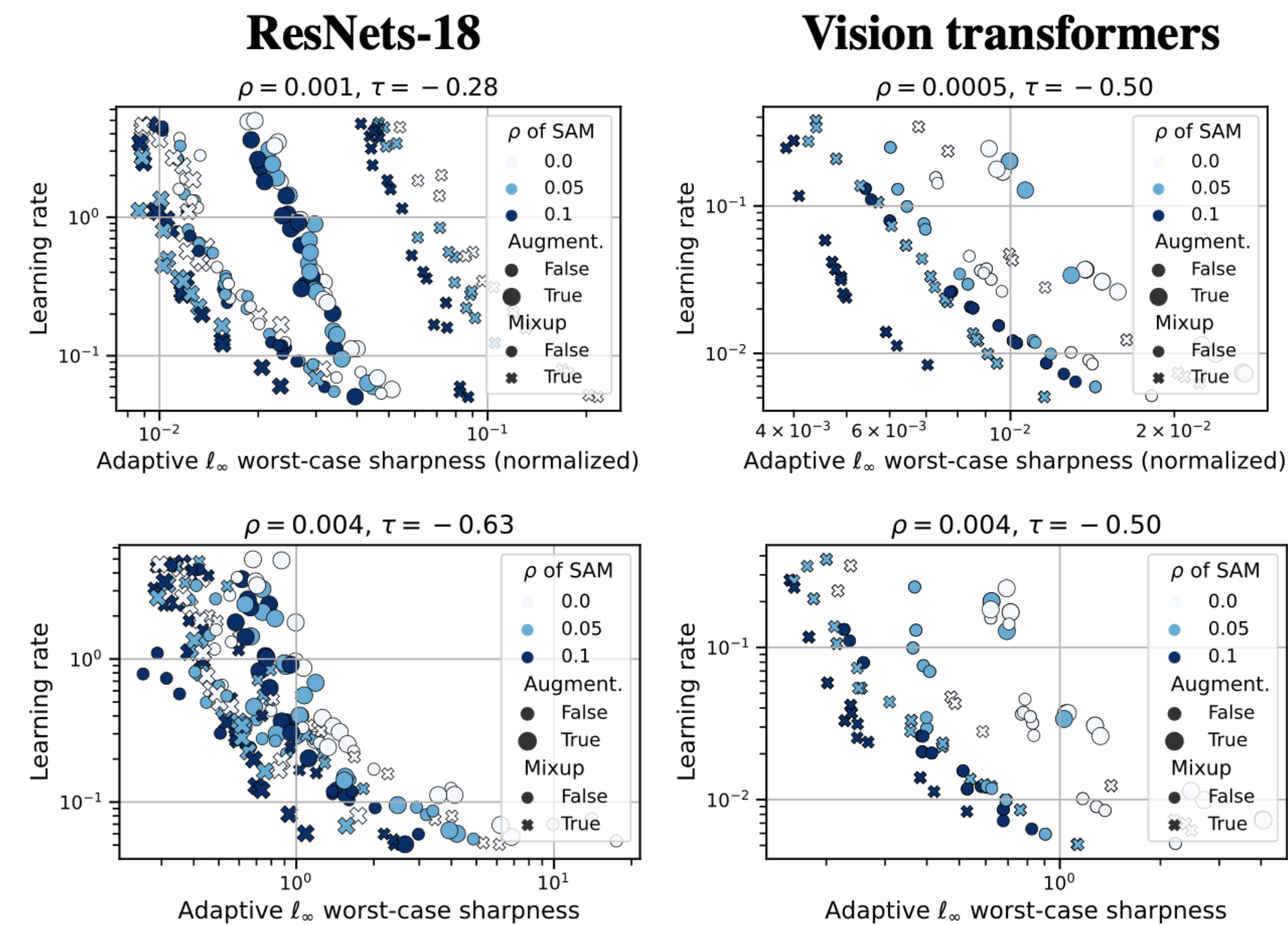
# Observations

- Order of magnitude difference in sharpness, but similar test error
- Still no support for strong or weak hypothesis





# Sharpness has strong -ve correlation to LR

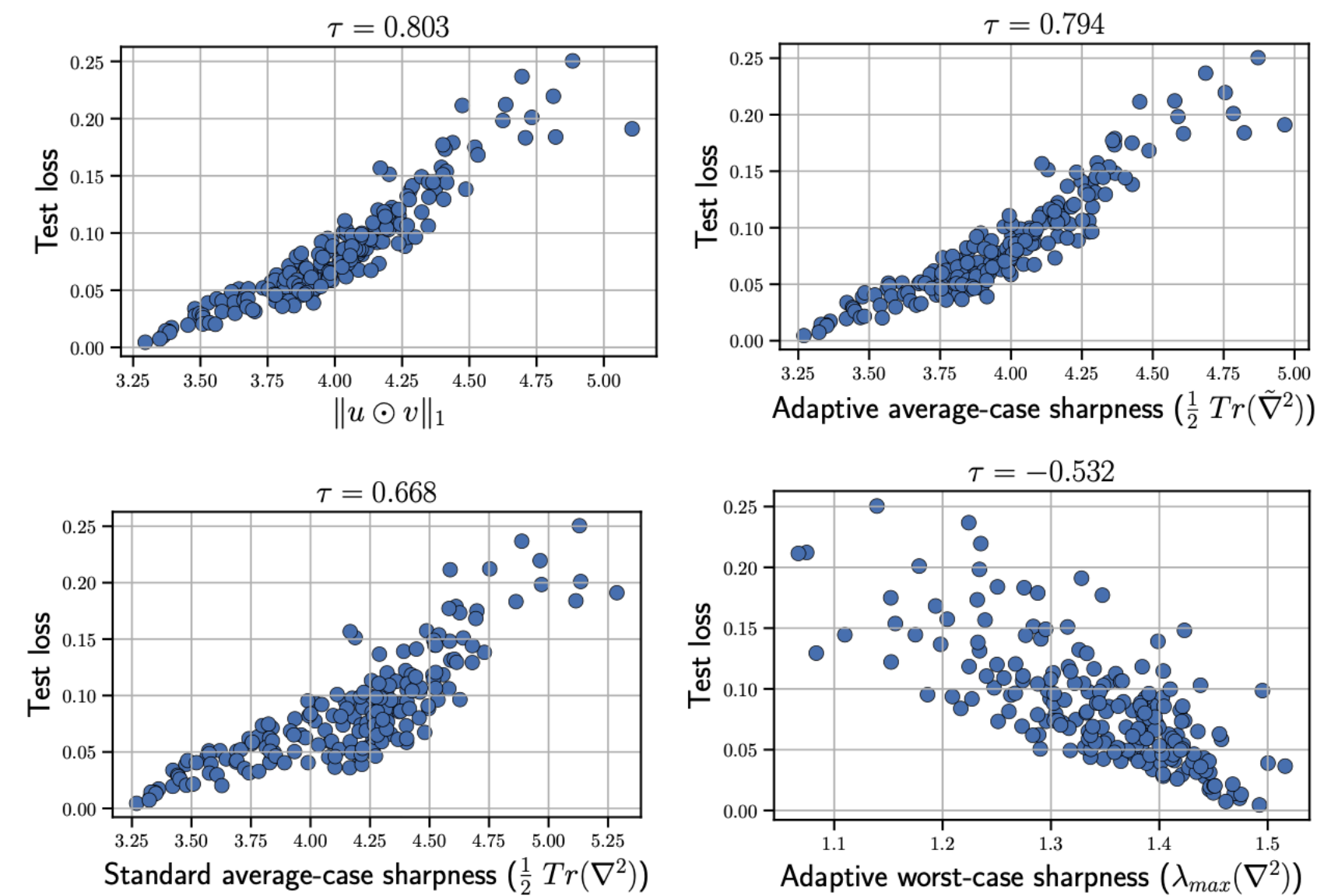


**Figure 6: Training from scratch on CIFAR-10.** Sharpness negatively correlates with the *learning rate*, especially within each subgroup defined by the same values of augment  $\times$  mixup.

# Is sharpness even the right measure?

Different sharpness measures have different generalization

- Well understood case of diagonal linear networks



**Figure 7: Different generalization measures for diagonal linear networks.**  $\tilde{\nabla}^2$  denotes the rescaled Hessian corresponding to adaptive sharpness.



# Conclusion

- In modern practical settings, sharpness does NOT imply generalization.
- In some setting, sharper minima can generalize better.
- On simple models and data we can understand well,  
there is no universal sharpness definition that predicts generalization.