



Australian
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On the Strong Correlation Between Model Invariance and Generalization

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Australian National University

Two Properties of a Machine Learning Model

Generalization

Classification ability on **unseen** data

Invariance

Robustness to input **transformation**

Generalization

Generalization captures a model's ability to **classify unseen** data

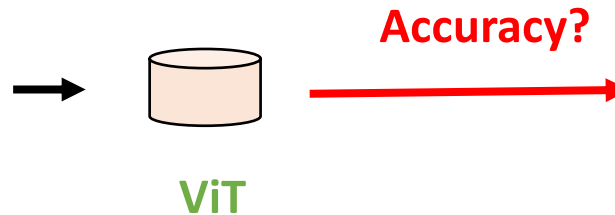
Generalization

Generalization captures a model's ability to **classify unseen** data

In-distribution Generalization



ImageNet Training Set



Generalization

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In-distribution Generalization

ImageNet-Val(idation)



Out-of-distribution Generalization

ImageNet-R(endiction)

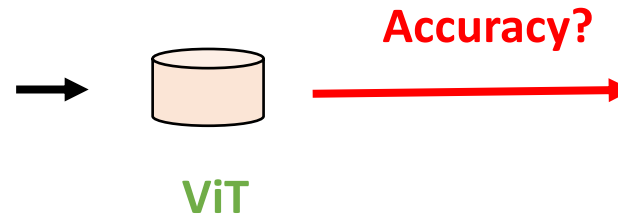


...

ImageNet-S(keetch)



ImageNet Training Set



Generalization

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In-distribution Generalization

ImageNet-Val(idation)



Model often performs **poorly** on datasets that have a **different distribution** from that of the training data

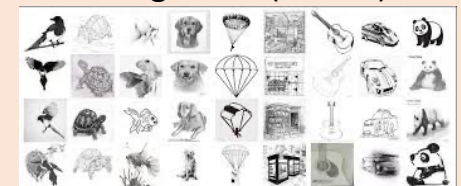


ImageNet Training Set

ViT



ImageNet-S(ketch)



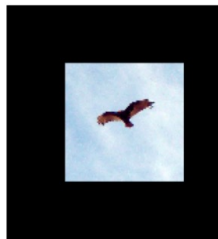
Invariance

Invariance measures how **consistent** model predictions are
on **transformed** test data

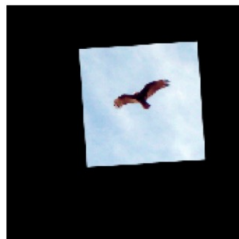
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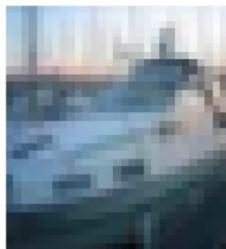
Transformed version



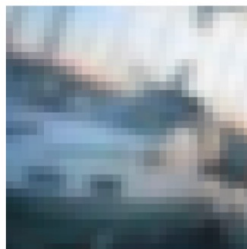
“vulture”



?



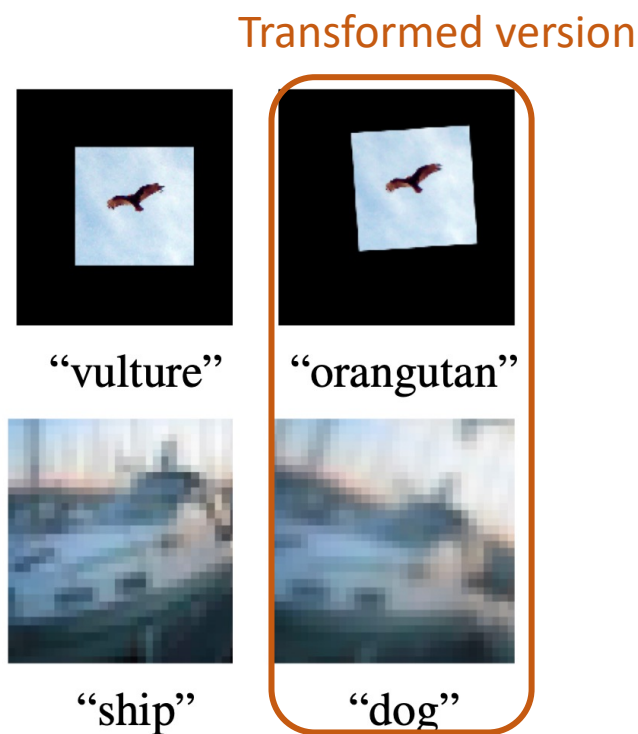
“ship”



?

Invariance

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State-of-the-art models turn out to be
vulnerable to translations and rotations

Relationship Between Invariance and Generalization

Generalization

Classification ability on unseen data

Invariance

Robustness to input transformation

Relationship



Insights From Existing Works

“adding **rotation invariance** to a model **improves** its in-distribution (**ID**) classification **accuracy**”

Zhou, Yanzhao, et al. "Oriented response networks." CVPR, 2017

Delchevalerie, Valentin, et al. "Achieving Rotational Invariance with Bessel-Convolutional Neural Networks." NeurIPS, 2021

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“a **shift-invariant** model is **robust to perturbation**”

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Zhang, Richard. "Making convolutional networks shift-invariant again." ICML, 2019

“theoretical investigations suggest that learning **invariant features** benefits **model generalization**”

Zhu, Sicheng, Bang An, and Furong Huang. "Understanding the Generalization Benefit of Model Invariance from a Data Perspective." NeurIPS, 2021

Relationship



Relationship Between Invariance and Generalization

Generalization

Invariance



Strong connection?

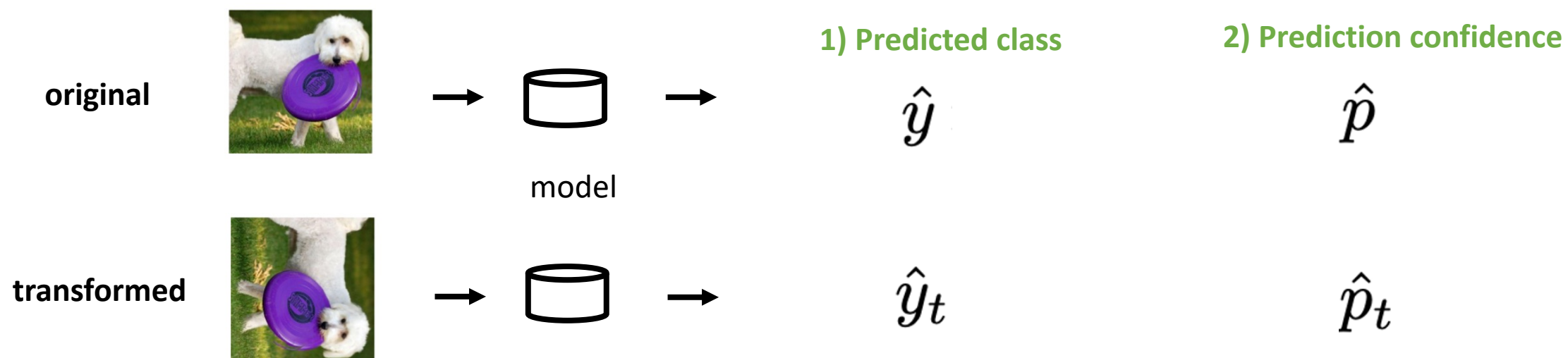
- Quantitative study

How to Measure?

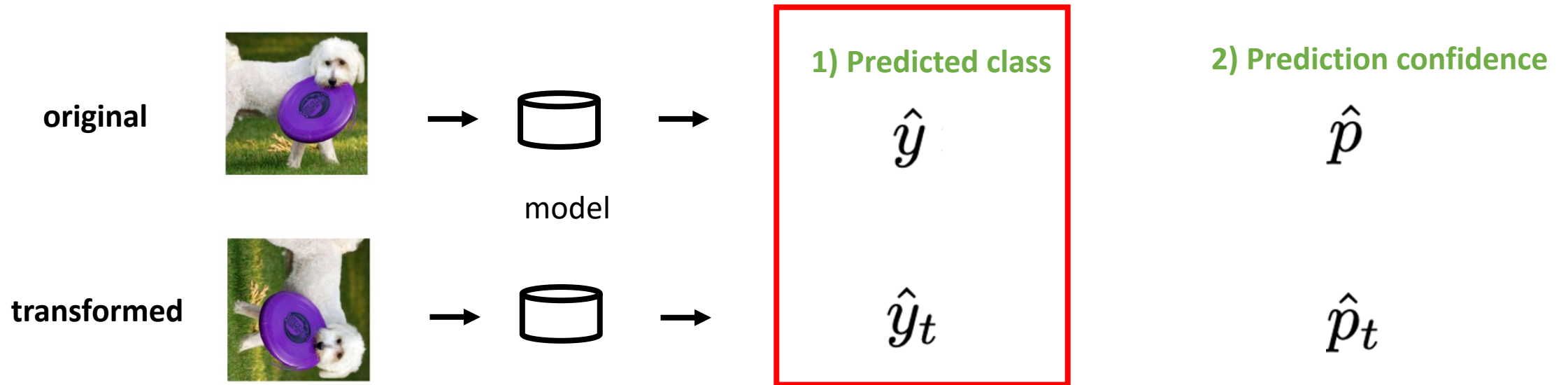
Generalization  **classification accuracy**

Invariance  **?**

Effective Invariance

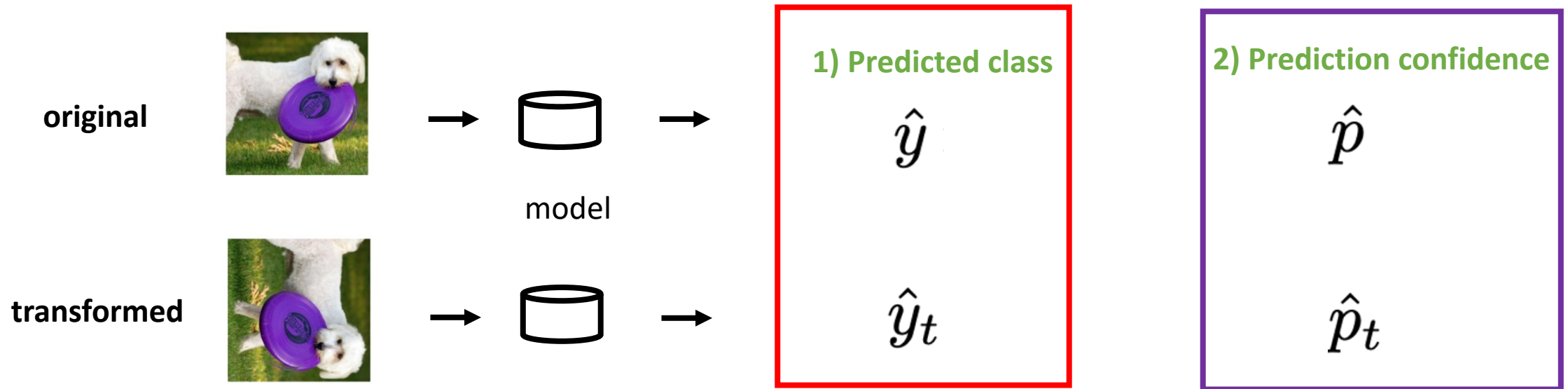


Effective Invariance



$$\text{EI}(\mathbf{x}, \mathcal{T}(\mathbf{x}), \mathbf{f}) = \begin{cases} \sqrt{\hat{p}_t \cdot \hat{p}} & \text{if } \underline{\hat{y}_t = \hat{y}}; \\ 0 & \text{otherwise.} \end{cases}$$

Effective Invariance



$$\text{EI}(\mathbf{x}, \mathcal{T}(\mathbf{x}), \mathbf{f}) = \begin{cases} \frac{\sqrt{\hat{p}_t \cdot \hat{p}}}{0} & \text{if } \hat{y}_t = \hat{y}; \\ 0 & \text{otherwise.} \end{cases}$$

Correlation Study: Models

ImageNet Setup

150 ImageNet models that are trained or finetuned on ImageNet training set

1) Standard neural networks: 100 models *only* trained on ImageNet training set

2) Semi-supervised learning: 15 models trained using a *large* collection of *unlabelled* images (e.g., Instagram 900M)

2) Pretraining on more data: 35 models that are *pre-trained* on significantly *larger datasets* (e.g., ImageNet-21K)

Correlation Study: Test Sets

ImageNet Setup

6 types of data distribution

In-Distribution: ImageNet-Val(idation)

Dataset reproduction shift: ImageNet-V2-A/B/C

Natural adversarial shift: ImageNet-Adv(ersarial)

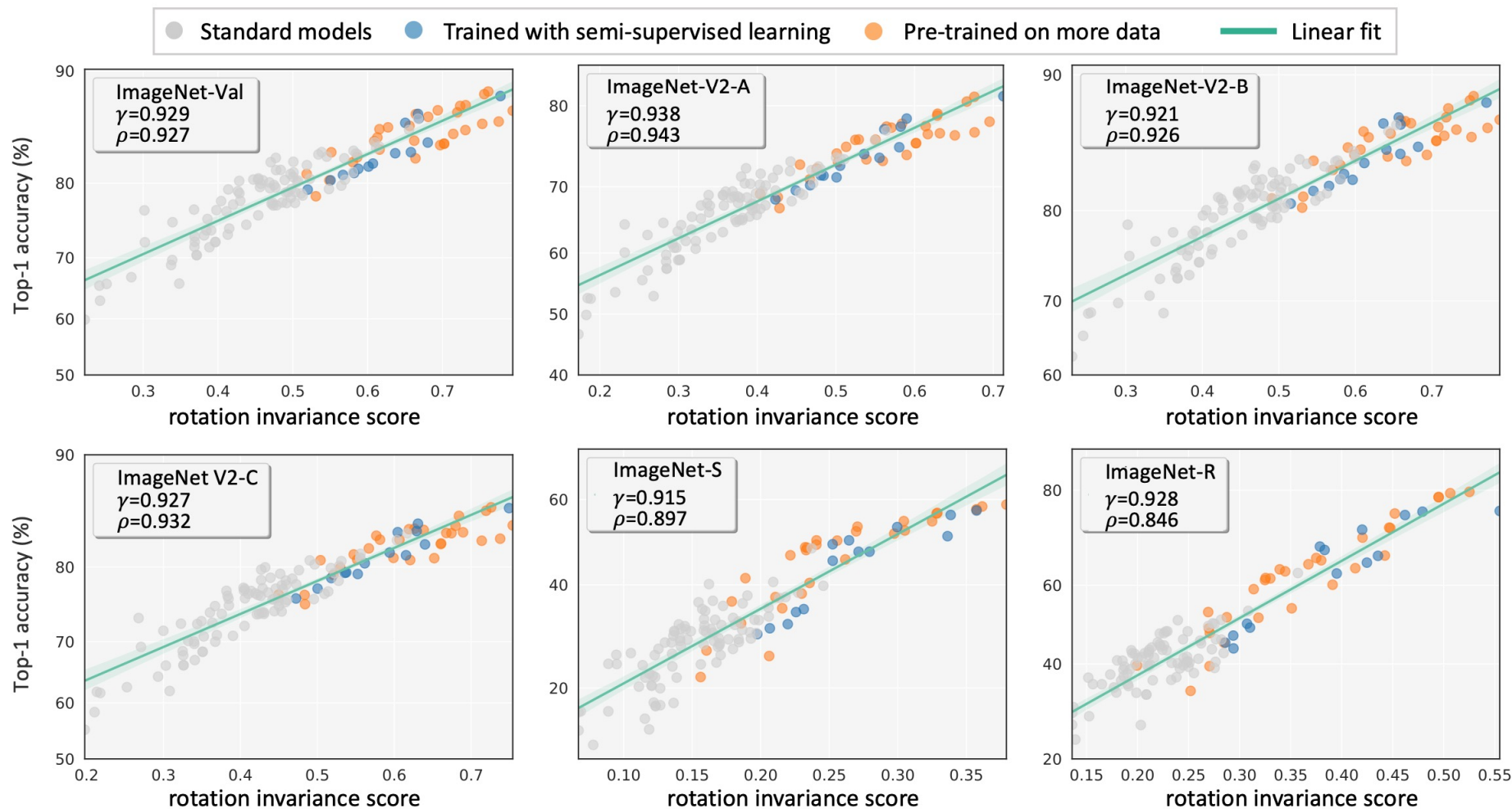
Sketch shift: ImageNet-S(ketch)

Blur shift: ImageNet-Blur that is synthesized by blurring ImageNet-Val

Style shift: ImageNet-R(endition)

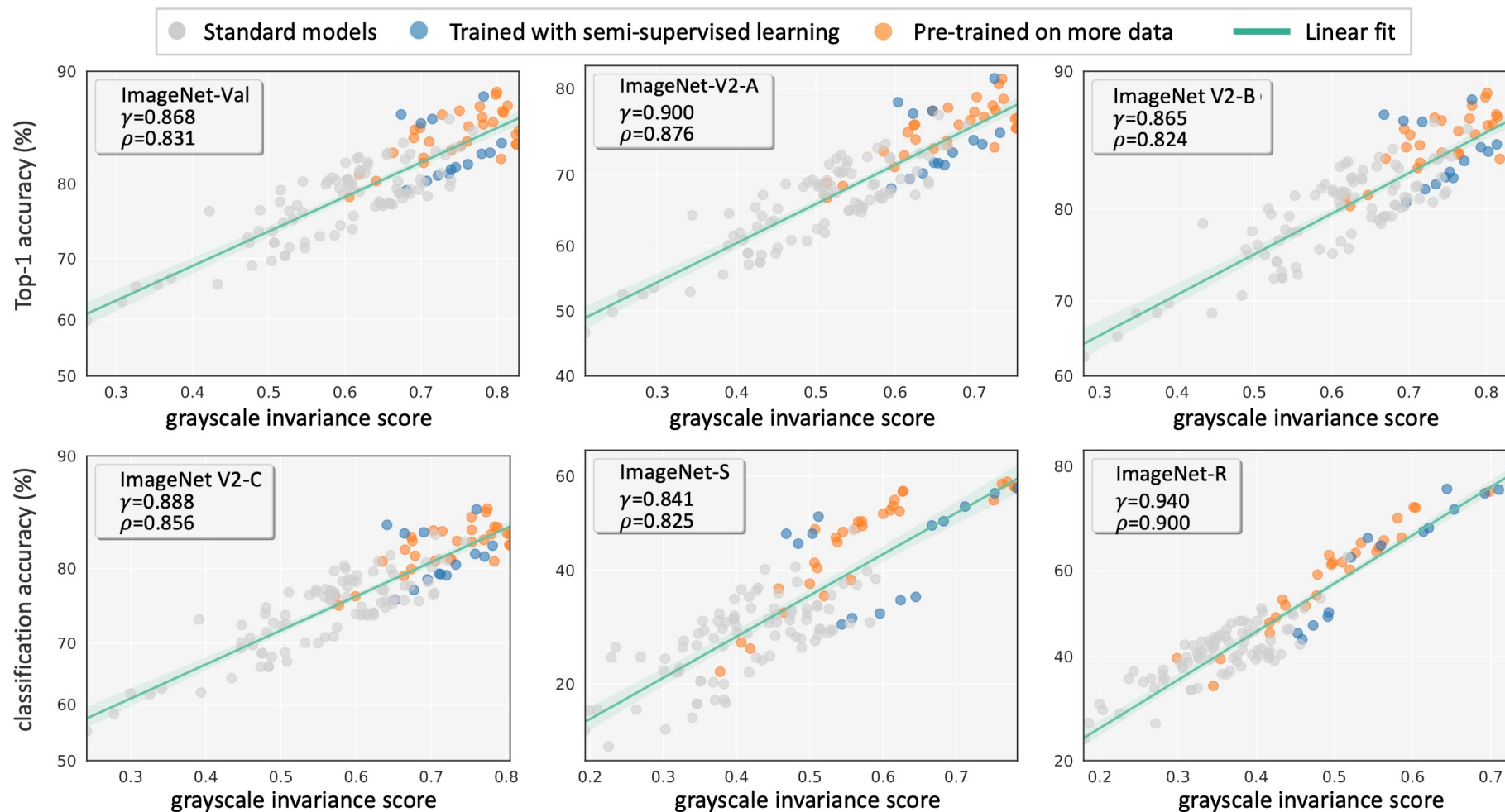
Correlation Study: Strong Correlation

Rotation Invariance

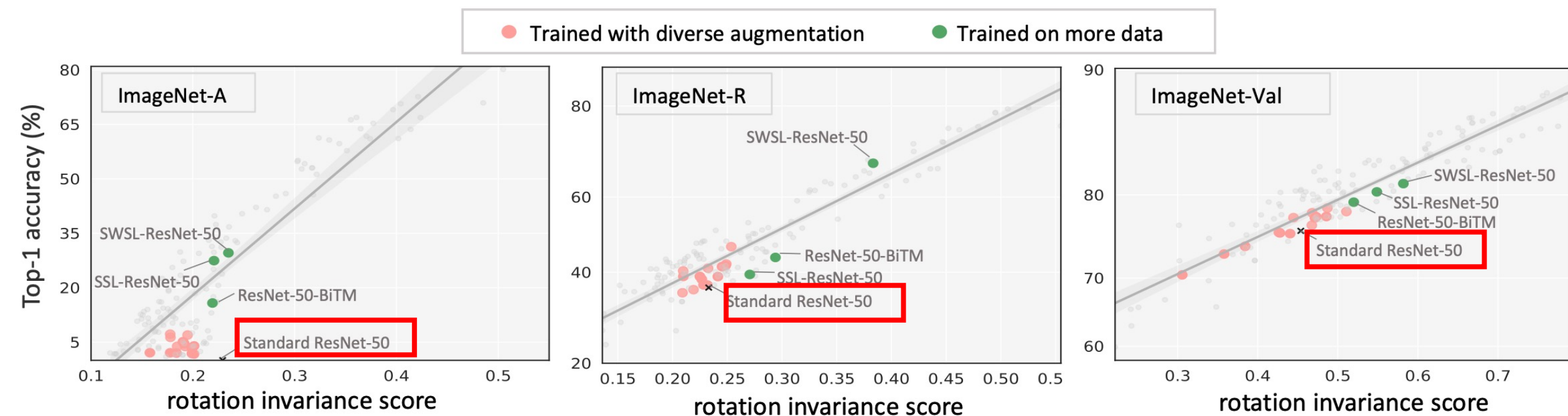


Correlation Study: Strong Correlation

Grayscale Invariance



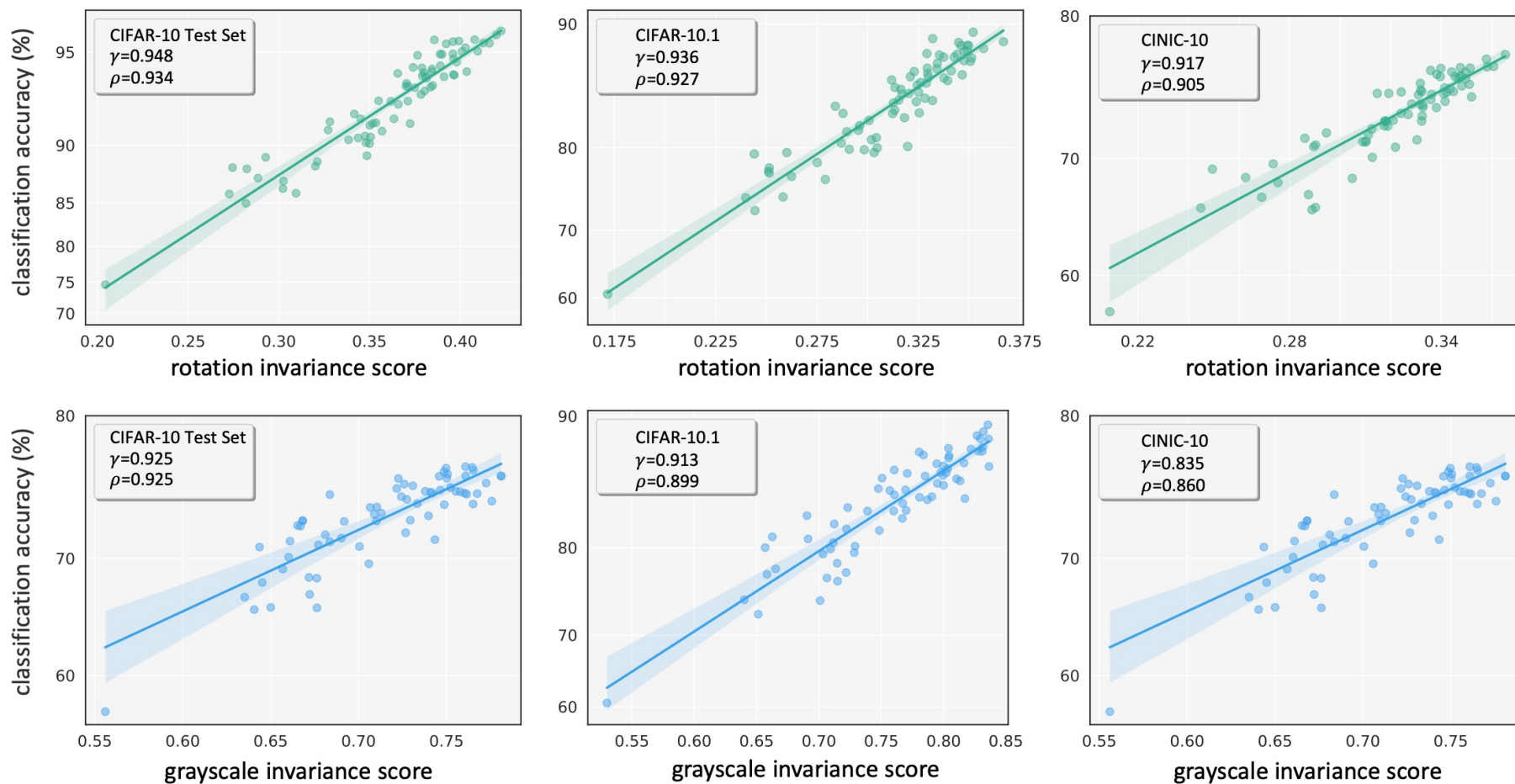
Data Augmentation vs. More Training Data



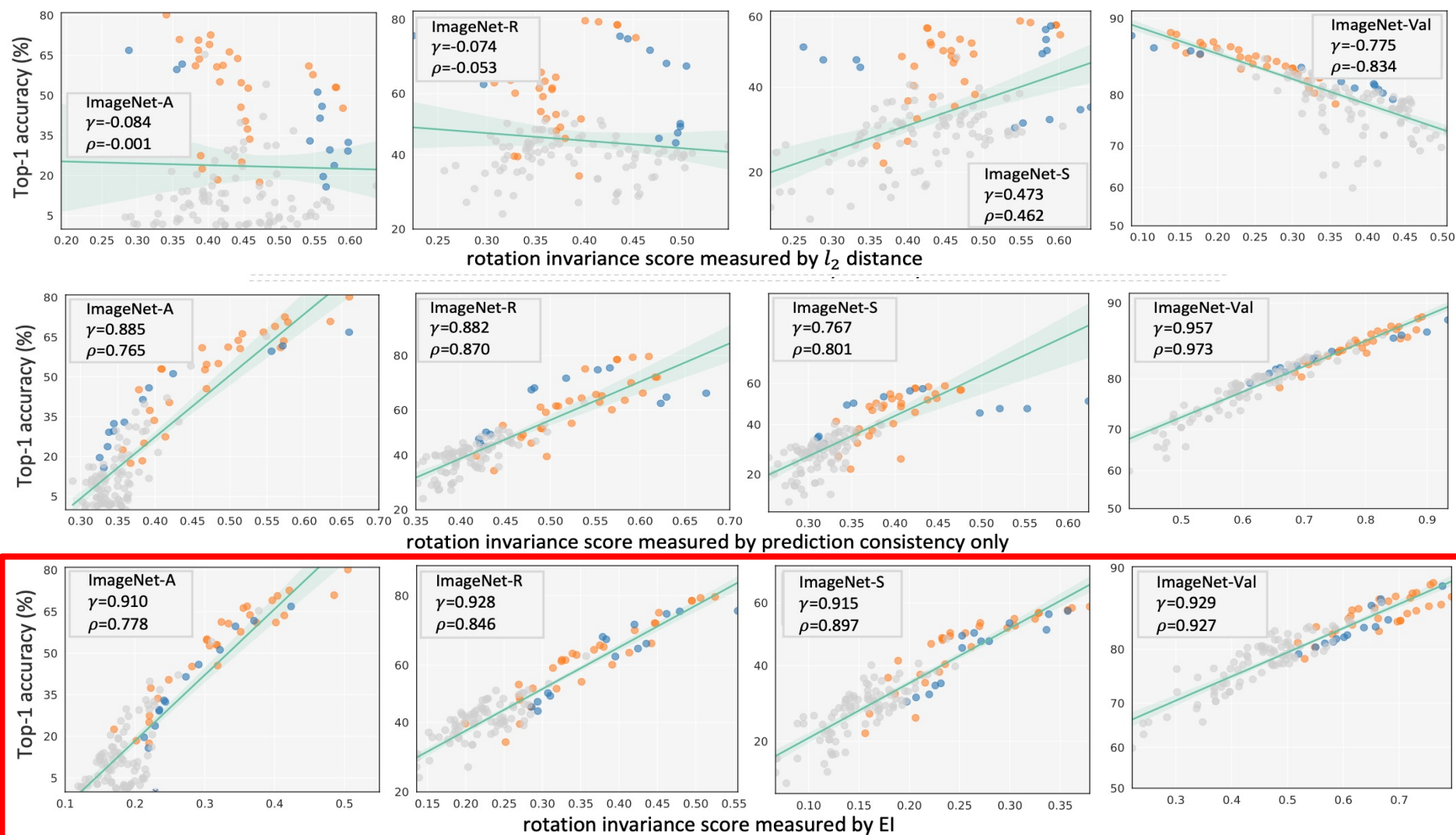
Training with more data allows models to achieve relatively high accuracy and invariance on three test sets

CIFAR-10 Setup

3 types of data distribution; 90 CIFAR-10 models



El Gives Stronger Correlation Strength Than Other Measures



Summary

- Effective invariance (EI) to more reasonably measure invariance
- Classification accuracy and EI of various models has a strong linear relationship on both ID and OOD datasets

Thank you!

For more information,
please refer to
<https://weijiandeng.xyz>

