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## Simplicity Bias and Domain Shifts

DNNs learn simple/biased shortcuts rather than complex/stable features.

Ex: to detect Covid, DNNs analyze body/shoulder positions rather than lung fields.

Negative image with shoulders moved



Important pixels



 $\Rightarrow$  lack of robustness, failures under shifts. Main challenge: we want to detect causation rather than correlation.

### Invariance Paradigm

Assumption: the causal mechanism is invariant across the various training domains.

How to enforce *invariance* across domains?

- In *features* extracted by the encoder  $f_{\phi}(x)$ . Ex: CORAL(AAAI16), DANN(JMLR16).
- In *predictors* with invariant risks  $l(f_{\theta}(x), y)$ . Ex: IRM, V-Rex(ICML21).
- In gradients of the loss w.r.t. the weights of the network  $\nabla_{\theta} l(f_{\theta}(x), y)$ . Ex: Fish(ICLR22).

# Fishr: Invariant Gradient Variances for **Out-of-Distribution Generalization**





Dataset	Domains											
Colored MNIST	+90% +80% -90% 3 3 3 5 (degree of correlation between color and label)	Algo. Inv	Invariance	Acc. $\uparrow$								Rank ↓
Rotated MNIST	$0^{\circ}$ $15^{\circ}$ $30^{\circ}$ $45^{\circ}$ $60^{\circ}$ $75^{\circ}$	U		CIVINIST	rMNIST	VLCS	PACS	OHome	Terral	DNet	Avg	Avg
	Caltech101 LabelMe SUN09 VOC2007	ERM X		57.8	97.8	77.6	86.7	66.4	<u>53.0</u>	41.3	68.7	9.1
VLCS		CORAL E	<b>4</b>	58.6	98.0	77.7	<u>87.1</u>	68.4	52.8	41.8	69.2	4.6
PACS	Art Cartoon Photo Sketch	DANN Fea	Features	57.0	<u>97.9</u>	<b>79.7</b>	85.2	65.3	50.6	38.3	67.7	11.9
Office-Home	Art Clipart Product Photo	IRM Pred	Predictors	<u>67.7</u>	97.5	76.9	84.5	63.0	50.5	28.0	66.9	14.7
	L100 L38 L43 L46	V-REx		67.0	<u>97.9</u>	78.1	87.2	65.7	51.4	30.1	68.2	7.7
Terra Incognita	(camera trap location)	Fish Gra	Gradients	61.8	<u>97.9</u>	77.8	85.8	66.0	50.8	43.4	69.1	8.4
DomainNet	Clipart Infographic Painting QuickDraw Photo Sketch   Image: A state of the sta	Fishr		68.8	97.8	<u>78.2</u>	86.9	<u>68.2</u>	53.6	<u>41.8</u>	70.8	3.9

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Fishr: Invariant Gradient Variances ... and also invariant risks and Hessians

 $\lambda$  controls the strength of our regularization matching the variance of gradients  $G_e = \left[ \nabla_{\theta} l\left( f_{\theta}(x_e^i), y_e^i \right) \right]_{i=1}^{n_e}$  across domains  $e \in \{A, B\}$ .

Theoretical analysis

Gradient variances as a proxy to match:

- risks:  $\mathcal{R}_e(\theta) = \sum_i l(f_\theta(x_e^i), y_e^i)/n_e$ ,
- Hessians:  $\mathcal{H}_e(\theta) = \sum_i \nabla_{\theta}^2 l(f_{\theta}(x_e^i), y_e^i)/n_e$ (proof via the Fisher Information Matrix).

We prove Fishr reduces *domain inconsistencies*:  $\mathcal{I}^{\varepsilon}(A,B) = \max_{\theta \in N_{A,\theta^*}} |R_B(\theta) - R_A(\theta^*)|$ in a  $\varepsilon$  neighbourhood  $N_{A,\theta^*}^{\varepsilon}$  around weights  $\theta^*$ .

State-of-the-art Performances on DomainBed Benchmark (at almost no computational overhead)



# $\mathcal{L}_{Fishr} = \mathcal{L}_{ERM} + \lambda \parallel Var(G_A) - Var(G_B) \parallel \frac{2}{2},$

