Learning Disentangled Representations for Environment Inference in Out-of-distribution Generalization

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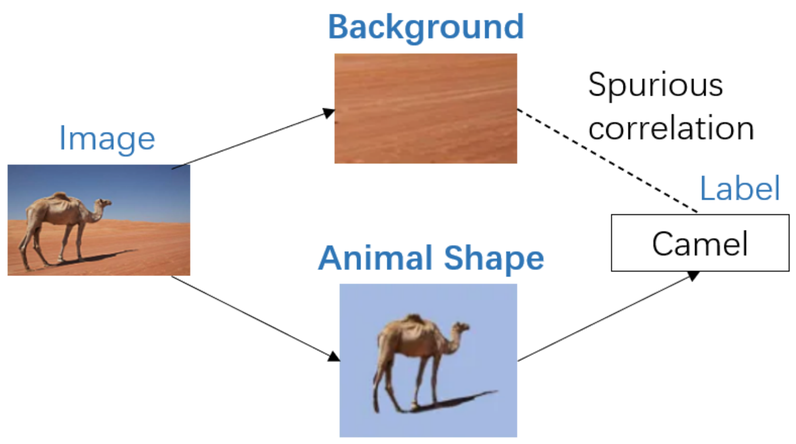
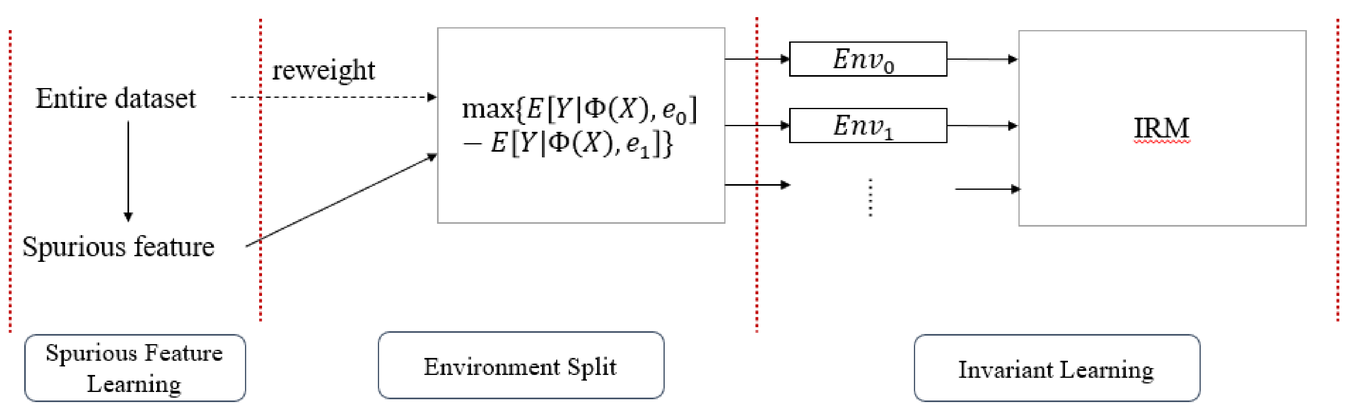
Problem

- **Out-of-distribution (OoD) generalization**: Machine learning models may suffer from a sharp drop under a distributional shift.
- Invariant Risk Minimization (IRM): Learn a stable correlation across multiple training environments.
- **Challenges:**
  - **Extra Environment Labels**: IRM requires predefined environment labels, which are not easily accessible.
  - **Improper Reference Model:** spurious features are employed to split datasets, but the quality of spurious features captured by the reference model is insufficient.
- **Our Contributions:**
  - Verifying that ERM-based methods cannot acquire sufficient spurious features.
  - VAE-based method as a reference model to learn disentangled spurious representations.





Proposed Method

- **Observations**

spurious features captured by ERM are insufficient by the two metric:

- Spurious Feature Score
- Invariant Penalty

Reference model	IP↑	SFS↑	Acc(%)↑
ERM	0.0007	0.32	18.8
Ours	**0.1052**	0.75	**63.8**
w/ EnvLabels	0.0025	**1.00**	57.3

- **Learning Disentangled Representations**

The classifier head only takes spurious features as input and the VAE decoder takes both spurious features and residual features as input.

$$ELBO(\phi,\theta,x) = \mathbb{E}_{z\sim q_\phi}\left[log\frac{p_\theta(x,z)}{q_\phi(z|x)}\right] \qquad \mathcal{L}(\phi,\theta,\varphi) = -\sum_{(x,y)\in\mathcal{D}_{tr}} ELBO(\phi,\theta,x) + \lambda\cdot log\, p_{\phi,\varphi}(y|x)$$

Experiments

Comparison with Existing Methods

Method	Env Labels	Train Accs	Test Accs
ERM	✘	**89.5 ± 1.1**	26.7 ± 2.8
EIIL	✘	75.2 ± 1.1	59.3 ± 5.5
Ours	✘	81.4 ± 0.3	**69.7 ± 1.8**
IRM	✔	76.7 ± 0.9	70.5 ± 2.2

Table 2: The performance evaluated on Colored MNIST[I].

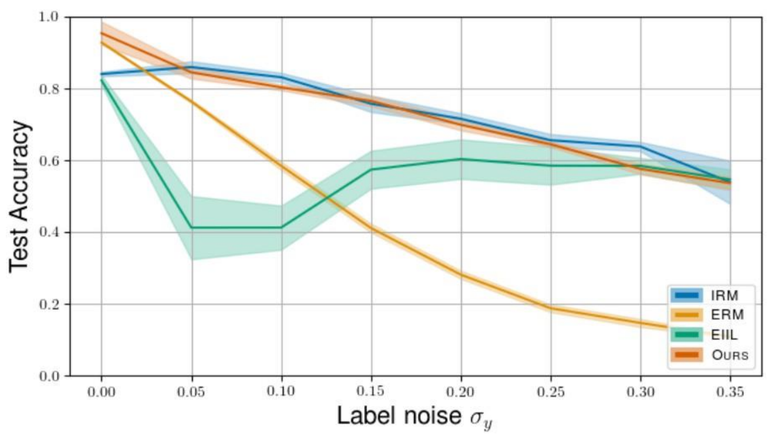
Method	Test Accs
ERM	56.9
EIIL	45.2
Ours	**63.8**
IRM(Oracle)	72.7

Table 3: The performance evaluated on Colored MNIST[II].

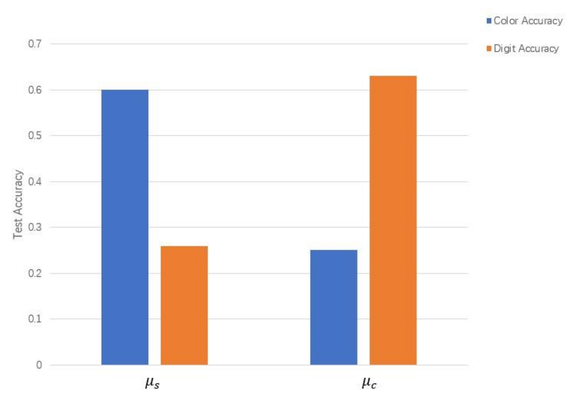
Method	Train Accs	Test Accs
ERM	**93.1 ± 5.9**	71.4 ± 3.4
DisEnt	15.5 ± 1.6	37.4 ± 2.4
ZIN	90.6 ± 0.3	70.8 ± 1.6
EIIL	78.2 ± 12.1	61.9 ± 4.9
Ours	80.4 ± 2.6	**74.4 ± 1.8**
IRM(Oracle)	83.2 ± 1.1	78.7 ± 0.8

Table 4: The performance evaluated on CelebA.

Robustness on label noise



Disentangled Representations Analysis



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