Meta-causal Learning for Single Domain Generalization

Jin Chen[1*], Zhi Gao[1*], Xinxiao Wu[1,2†], Jiebo Luo[3]
[1]Beijing Key Laboratory of Intelligent Information Technology,
School of Computer Science & Technology, Beijing Institute of Technology, China
[2]Guangdong Laboratory of Machine Perception and Intelligent Computing,
Shenzhen MSU-BIT University, China
[3]Department of Computer Science, University of Rochester, Rochester NY 14627, USA
{chen_jin,gaozhi_2017,wuxinxiao}@bit.edu.cn, jluo@cs.rochester.edu

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Motivation

- Existing methods focus on expanding the distribution of the source domain to cover the target domains, but without estimating the domain shift between the source and target domains.
- Learn to analyze the cause of the domain shift across different domains
- Learn to reduce the domain shift according to it causes

Motivation

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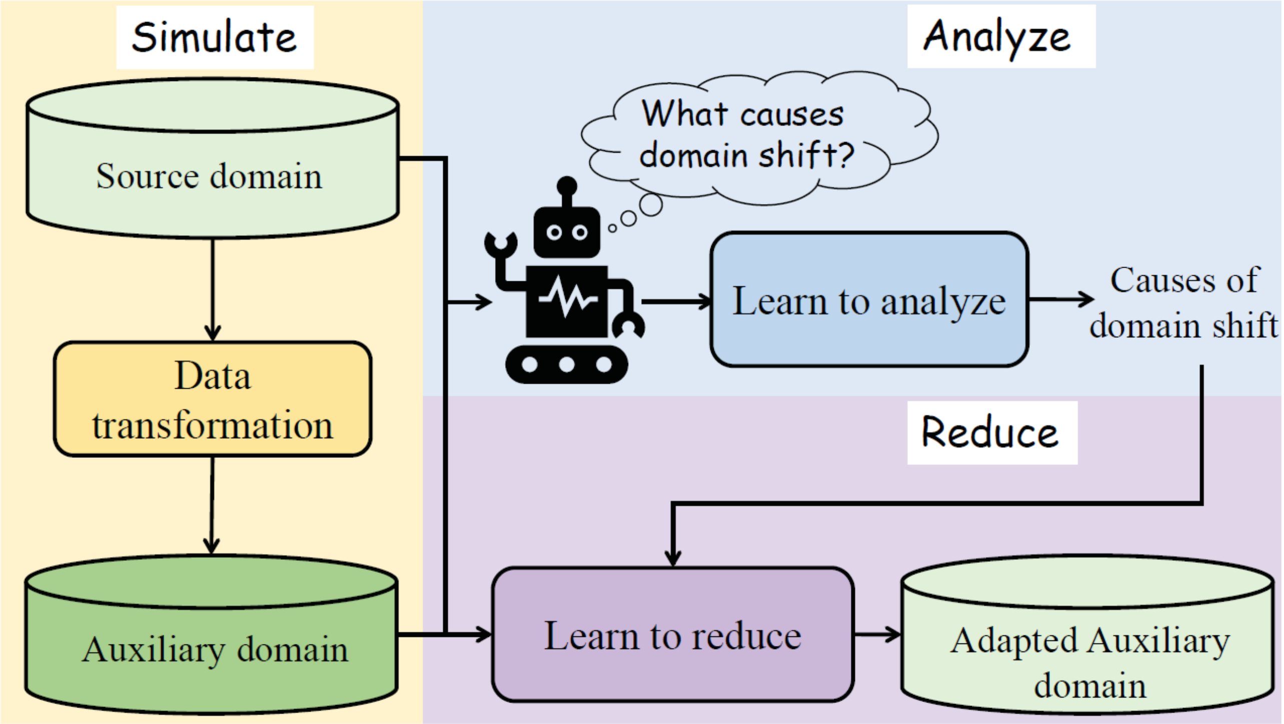
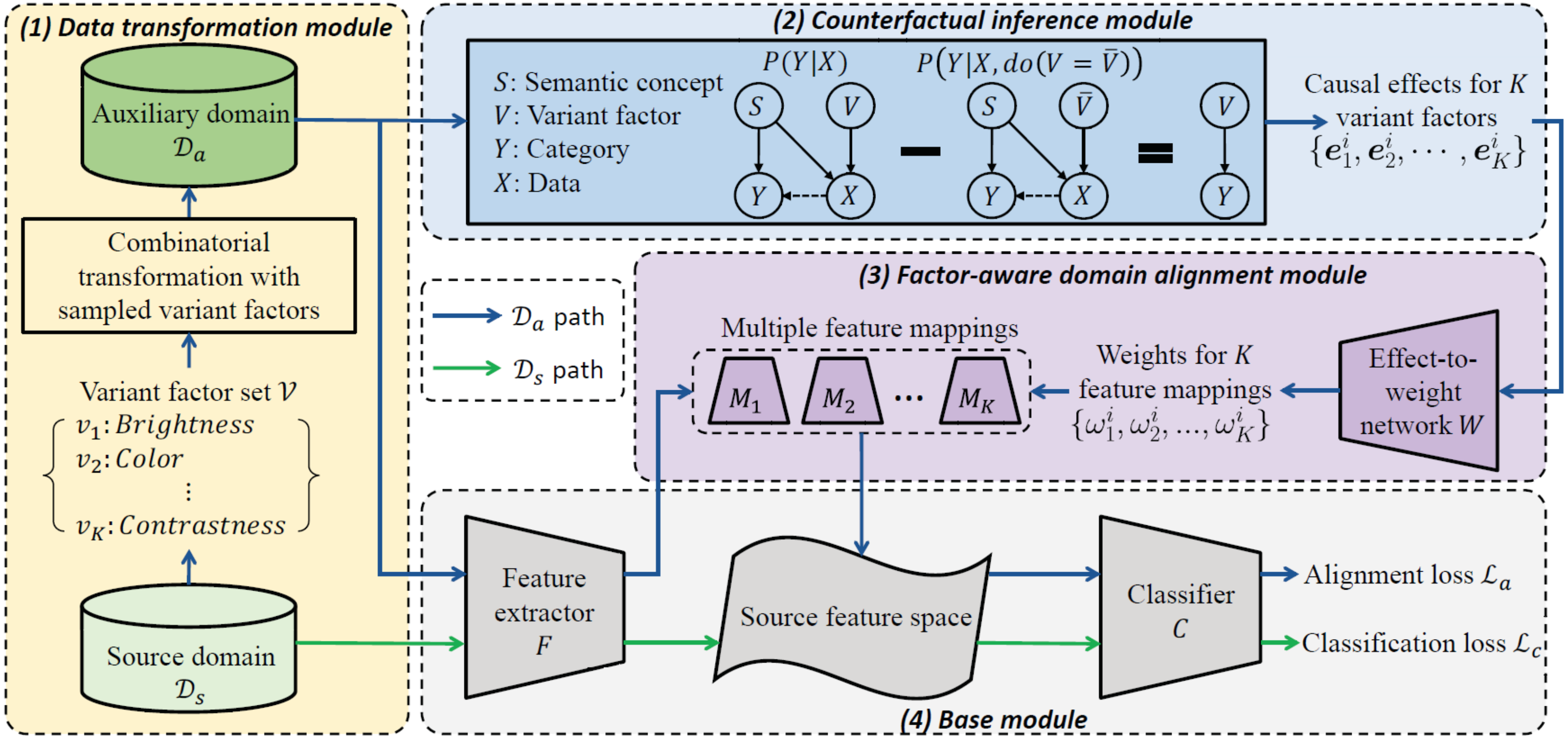
- ***Simulate-analyze-reduce paradigm***

1. Simulate the domain shift by building an auxiliary domain as the target domain
2. Learn to analyze the causes of domain shift
3. Learn to reduce the domain shift for model adaptation



Framework



(1) data transformation module: generate auxiliary domains as target domains
(2) counterfactual inference module: discover the causes of the domain shift
(3) factor-aware domain alignment module: reduce the domain shift
(4) base module: feature extraction and classification.

Data Transformation for Domain Shift Simulation

- Variant factor set: $\mathcal{V}=\{v_1, v_2, \cdots v_K\}$
- For the k-th variant factor v_k, the corresponding data transformation function is denoted as $G_{v_k}(x;\theta_{v_k})$, θ_{v_k} represents the degree parameter to control the magnitude of transformation.
- Given source sample x_i^s, we randomly sample N_v^i variant factors from $\mathcal{V}$ to generate auxiliary sample x_i^a:

$$\boldsymbol{x}_i^a = G_{v^i_{N_v^i}}\left(\cdots G_{v_2^i}\left(G_{v_1^i}\left(\boldsymbol{x}_i^s;\theta_{v_1^i}\right);\theta_{v_2^i}\right)\cdots;\theta_{v^i_{N_v^i}}\right)$$

Counterfactual Inference for Domain Shift Analysis

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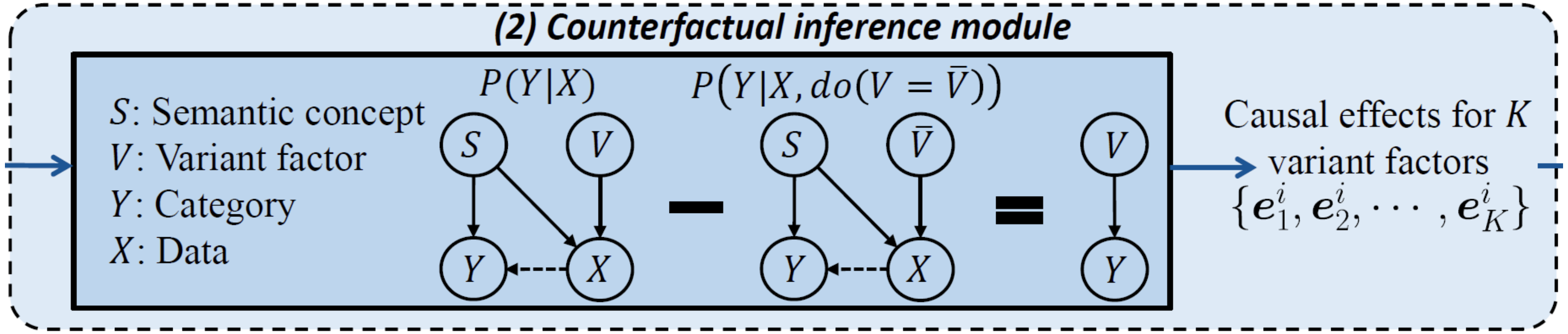

- Causes of the domain shift $V \rightarrow X \rightarrow Y$, infer the causal effect of V on Y

$$\boldsymbol{y}_i^a = P(Y|X) = C(F(\boldsymbol{x}_i^a))$$

$$\boldsymbol{y}_{i,v_k}^a = P\big(Y|X, do(V = v_k)\big) = \frac{1}{|\mathcal{M}|} \sum_{\theta_{v_k} \in \mathcal{M}} C\Big(F\big(G_{v_k}(\boldsymbol{x}_i^a; \theta_{v_k})\big)\Big)$$

$$\boldsymbol{e}_k^i = P(Y|X) - P\big(Y|X, do(V = v_k)\big) = \boldsymbol{y}_i^a - \boldsymbol{y}_{i,v_k}^a$$

Factor-aware Domain Alignment for Domain Shift Reduction

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- Learn multiple feature mappings $\{M_i\}_{i=1}^{K}$
- The k-th feature mapping aims to address the domain shift caused by the k-th variant factor
- Effect-to-weight network W: convert the causal effect of each variant factor into the weight of the corresponding feature mapping

$$\mathcal{L}_a^c = \underbrace{\frac{1}{N_s}\sum_i ||F(\boldsymbol{x}_i^s) - \sum_k \omega_k^i M_k(F(\boldsymbol{x}_i^a))||_2}_{\text{Feature distance}}$$

$$+ \underbrace{\frac{1}{N_s}\sum_i \mathcal{H}\Big(C\Big(\sum_k \omega_k^i M_k(F(\boldsymbol{x}_i^a)), y_i^s\Big)\Big)}_{\text{Classification}}$$

Experiments

Table 1. Single domain generalization results (%) on Digits with ConvNet as backbone. The model is trained on MNIST, and evaluated on SVHN, SYN, MNIST-M, and USPS.

Method	SVHN	SYN	MNIST-M	USPS	Avg
ERM [14]	27.83	39.65	52.72	76.94	49.29
CCSA [24]	25.89	37.31	49.29	83.72	49.05
d-SNE [36]	26.22	37.83	50.98	**93.16**	52.05
JiGen [2]	33.80	43.79	57.80	77.15	53.14
GUD [31]	35.51	45.32	60.41	77.26	54.62
M-ADA [28]	42.55	48.95	67.94	78.53	59.49
ME-ADA [37]	42.56	50.39	63.27	81.04	59.32
PDEN [19]	62.21	69.39	82.20	85.26	74.77
L2D [34]	62.86	63.72	**87.30**	83.97	74.46
AA [4]	45.23	64.52	60.53	80.62	62.72
RA [5]	54.77	59.60	74.05	77.33	66.44
RSDA [30]	47.40	62.00	81.50	83.10	68.50
RSDA+ASR [8]	52.80	64.50	80.80	82.40	70.10
Ours	**69.94**	**78.47**	78.34	88.54	**78.82**

Table 2. Single domain generalization results (%) on CIFAR10-C with WRN as backbone. Each level is viewed as a target domain, a higher level denotes the more serious corruption and the domain discrepancy between the source and target domains is larger.

Method	level1	level2	level3	level4	level5	Avg
ERM [14]	87.80	81.50	75.50	68.20	56.10	73.82
GUD [31]	88.30	83.50	77.60	70.60	58.30	75.66
M-ADA [28]	90.50	86.80	82.50	76.40	65.60	80.36
PDEN [19]	90.62	88.91	87.03	83.71	77.47	85.55
AA [4]	91.42	87.88	84.10	78.46	71.13	82.60
RA [5]	91.74	88.89	85.82	81.03	74.93	84.48
Ours	**92.38**	**91.22**	**89.88**	**87.73**	**84.52**	**89.15**

Table 3. Single domain generalization results (%) on PACS with ResNet-18 as backbone. One domain (name in column) is used as the source domain and the other three domains are used as the target domains.

Method	Artpaint	Cartoon	Sketch	Photo	Avg
ERM [14]	70.90	76.50	53.10	42.20	60.70
RSC [12]	73.40	75.90	56.20	41.60	61.80
RSC+ASR [8]	76.70	79.30	61.60	54.60	68.10
Ours	**77.13**	**80.14**	**62.55**	**59.60**	**69.86**

Experiments

Figure 4. Examples of the inferred causal effects (represented as weights) of variant factors. The left part shows a source image from the CIFAR10 dataset and three target images from the CIFAR10-C dataset with Gaussian noise corruption. As the corruption severity increases from level 1 to level 5, the inferred weights of the *NoiseGaussian* variant factor become larger accordingly.

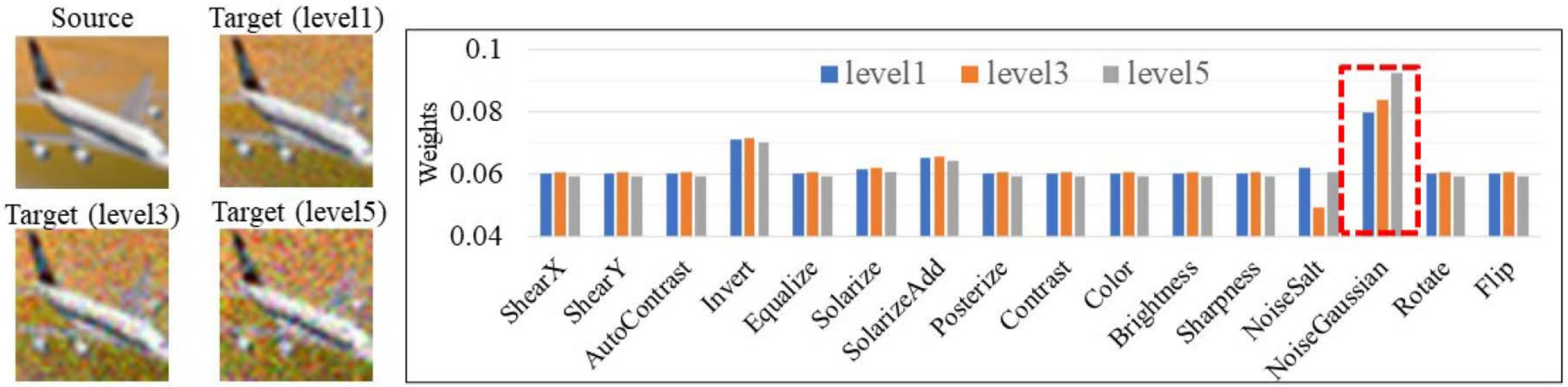

Table 5. Ablation study (%) on PACS with ResNet-18 as backbone. One domain (name in column) is used as the source domain and the other three domains are used as target domains. "T", "A", "C" denote Domain Transformation, Domain Alignment, and Counterfactual Inference, respectively.

Method	T	A	C	Artpaint	Cartoon	Sketch	Photo	Avg
Base				71.26	67.64	43.97	36.99	54.97
DT	✓			75.28	78.46	59.45	56.09	67.32
DTA	✓	✓		71.64	72.78	57.11	52.02	63.39
Ours	✓	✓	✓	**77.13**	**80.14**	**62.55**	**59.60**	**69.86**

Summary

- We have presented a new paradigm, ***simulate-analyze-reduce***, which empowers the model with the ability to analyze the domain shift, instead of directly expanding the distribution of the source domain to cover unseen target domains.
- We have presented a ***meta-causal learning*** method that can learn meta-knowledge about inferring the causes of domain shift during training, and apply such meta-knowledge to reduce the domain shift for boosting adaptation during testing.

Thank you