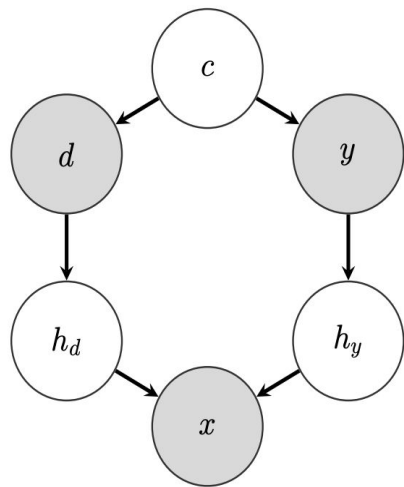


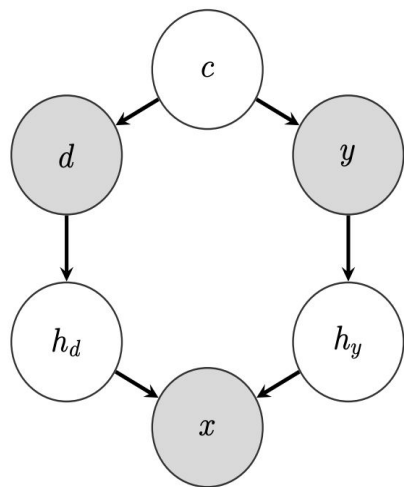
# Selecting Data Augmentation for Simulating Interventions

Maximilian Ilse, Jakub M. Tomczak, Patrick Forré

# Domain Generalization

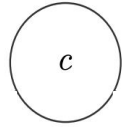


# Domain Generalization



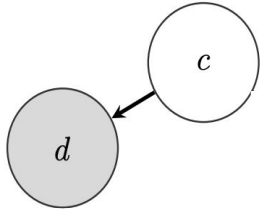
	Train			Val (OOD)	Test (OOD)
	$d = \text{Hospital 1}$	$d = \text{Hospital 2}$	$d = \text{Hospital 3}$	$d = \text{Hospital 4}$	$d = \text{Hospital 5}$
$y = \text{Normal}$					
$y = \text{Tumor}$					

# Domain Generalization



*c* confounder: geographical location

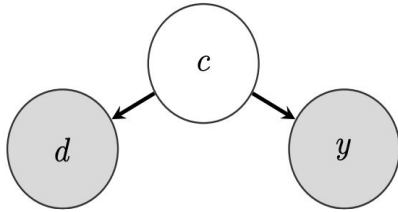
# Domain Generalization



$c$  confounder: geographical location

$d$  domain: hospital

# Domain Generalization

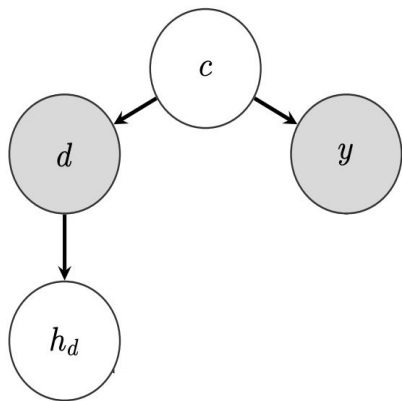


$c$  confounder: geographical location

$d$  domain: hospital

$y$  label: disease

# Domain Generalization



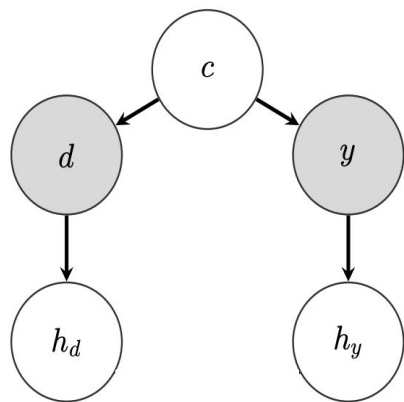
$c$  confounder: geographical location

$d$  domain: hospital

$y$  label: disease

$h_d$  high level features caused by  $d$ : color

# Domain Generalization



$c$  confounder: geographical location

$d$  domain: hospital

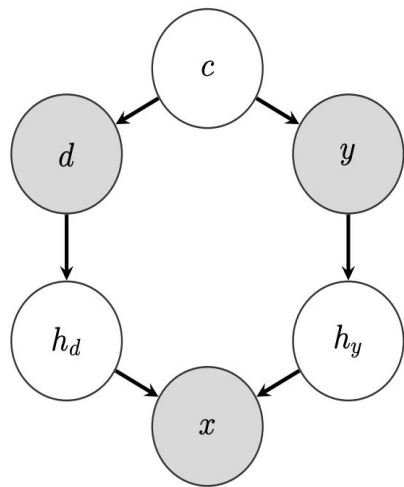
$y$  label: disease

$h_d$  high level features caused by  $d$ : color

$h_y$  high level features caused by  $y$ : morphology



# Domain Generalization



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$d$  domain: hospital

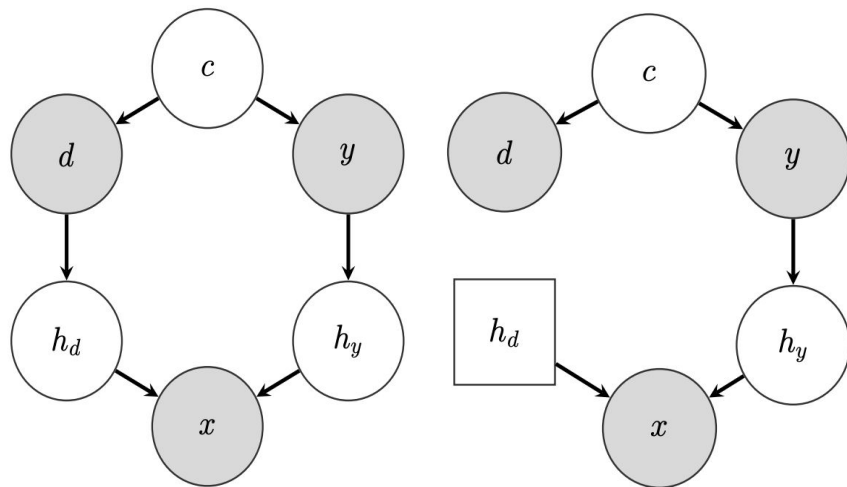
$y$  label: disease

$h_d$  high level features caused by  $d$ : color

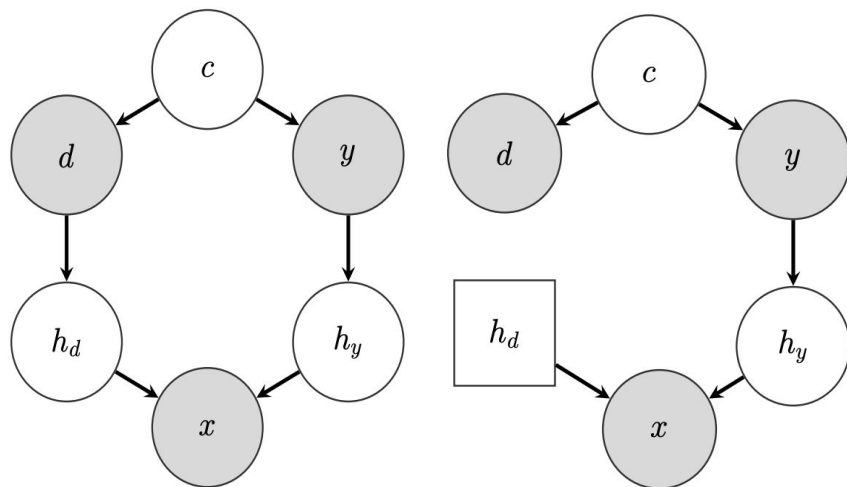
$h_y$  high level features caused by  $y$ : morphology

$x$  observation: image

# Intervention



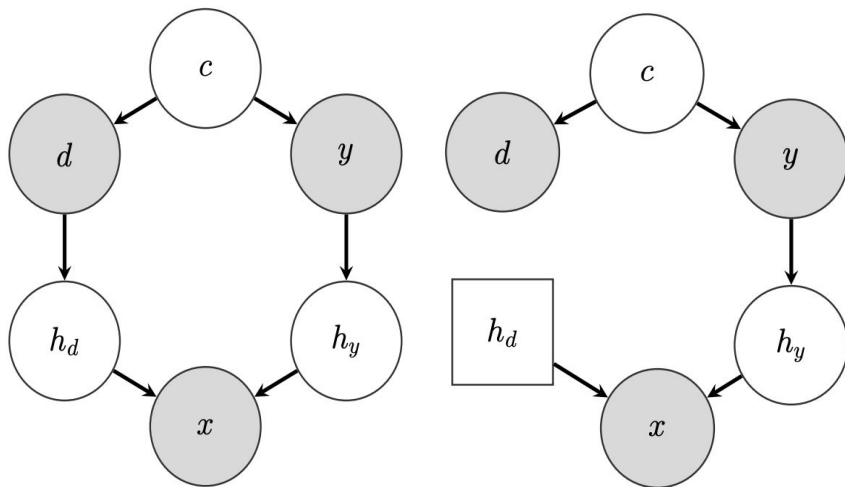
# Intervention



Noise intervention:

$\text{do}(\mathbf{h}_d = \xi)$ , where  $\xi \sim N_\xi$

# Intervention

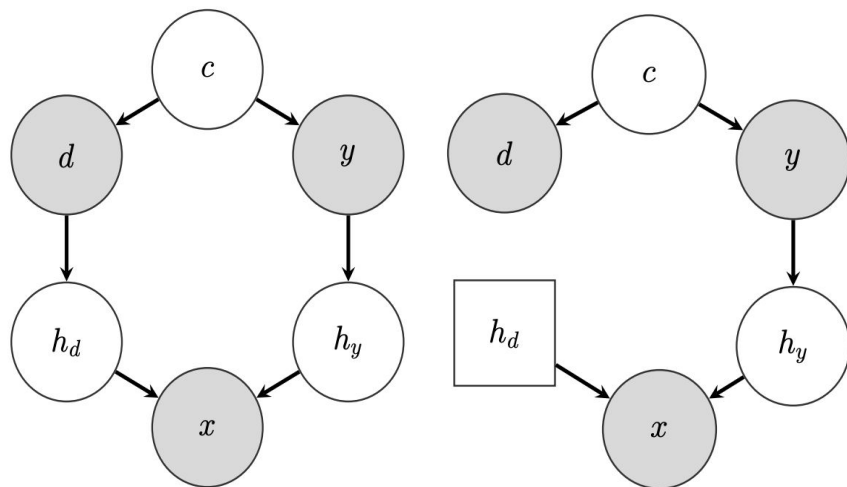


Noise intervention:

$\text{do}(\mathbf{h}_d = \xi)$ , where  $\xi \sim N_\xi$

Removes spurious correlation

# Intervention



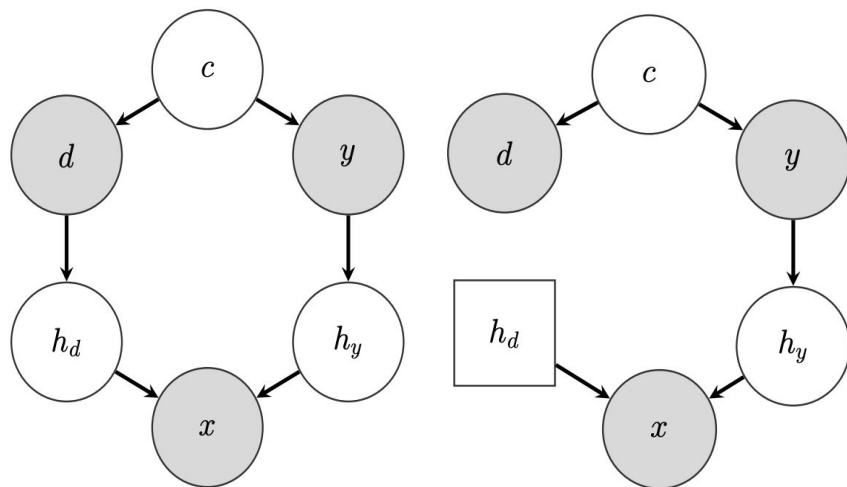
Noise intervention:

$\text{do}(\mathbf{h}_d = \xi)$ , where  $\xi \sim N_\xi$

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Interventions need to happen in the real world

# Intervention



Noise intervention:

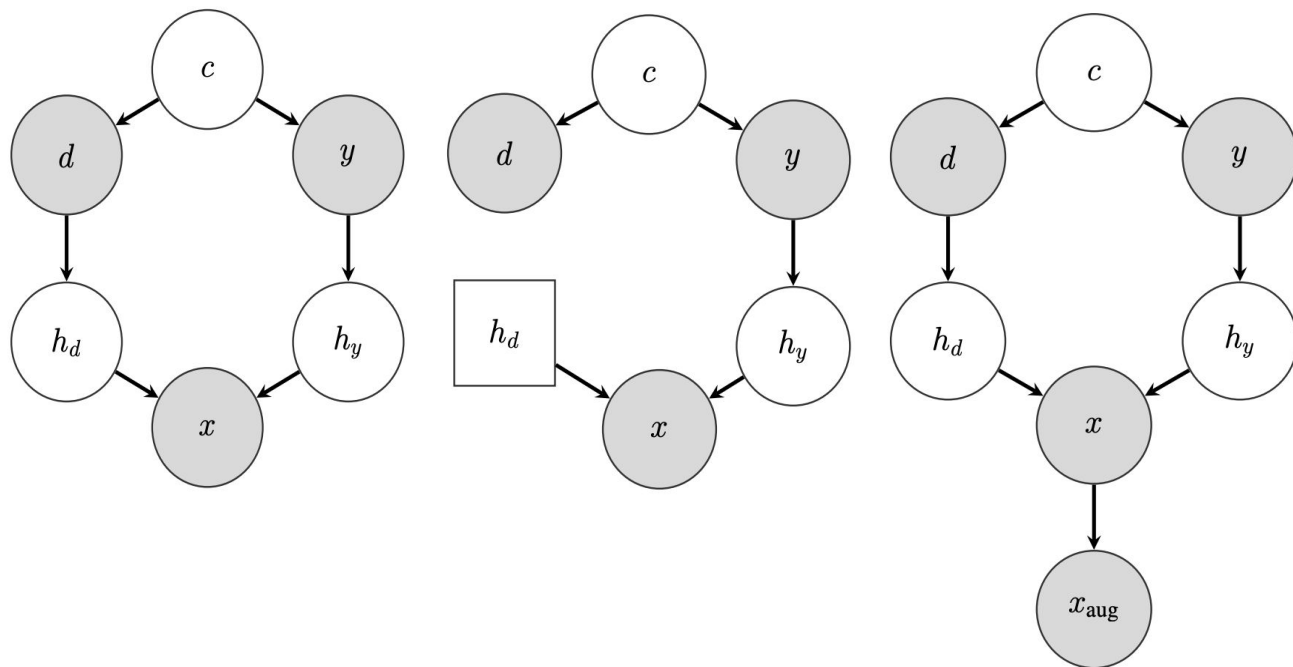
$\text{do}(\mathbf{h}_d = \xi)$ , where  $\xi \sim N_\xi$

Removes spurious correlation

Interventions need to happen in the real world

Data Augmentation

# Data augmentation



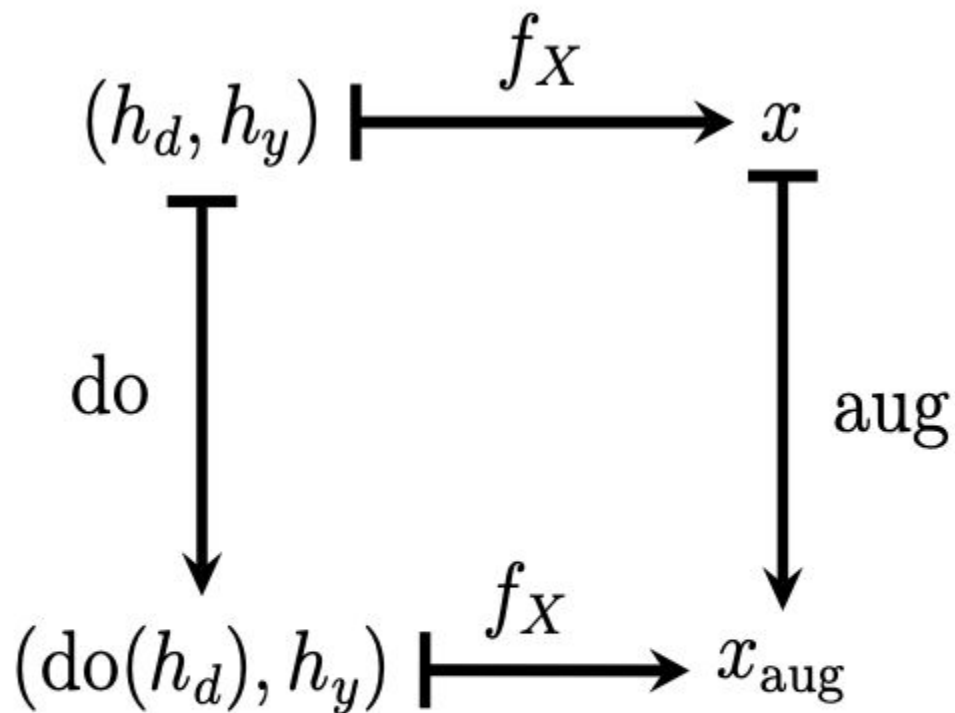


Figure 3: Intervention-augmentation equivariance expressed in a commutative diagram.



# Select Data Augmentation (SDA)

Table 1: Results on Rotated MNIST results. Average accuracy for ten seeds.

Target	ERM	DANN	CDANN	SDA
0°	75.4	77.1	78.5	<b>96.1</b>
30°	93.4	94.2	94.9	<b>95.9</b>
60°	94.5	95.2	95.6	<b>95.7</b>
90°	79.6	83.0	84.0	<b>95.9</b>
Ave	85.7	87.4	88.3	<b>95.9</b>

Table 3: Results on Colored MNIST. Average accuracy  $\pm$  standard deviation for ten seeds.

Acc	ERM	IRM	REx	SDA
Train	<b>87.4 <math>\pm</math> 0.2</b>	70.8 $\pm$ 0.9	71.5 $\pm$ 1.0	72.1 $\pm$ 0.4
Test	17.1 $\pm$ 0.6	66.9 $\pm$ 2.5	68.7 $\pm$ 0.9	<b>74.1 <math>\pm</math> 0.9</b>

Table 2: Results on PACS dataset. Average accuracy for five seeds.

Target	ERM	CDANN	L2G	GLCM	SSN	IRM	REx	MetaReg	JigSaw	SDA
A	63.3	62.7	66.2	66.8	64.1	67.1	67.0	69.8	67.6	<b>70.45</b>
C	63.1	69.7	66.9	69.7	66.8	68.5	68.0	70.4	<b>71.7</b>	68.49
P	87.7	78.7	88.0	87.9	90.2	89.4	89.7	<b>91.1</b>	89.0	88.35
S	54.1	64.5	59.0	56.3	60.1	57.8	59.8	59.3	65.2	<b>72.24</b>
Ave	67.1	68.9	70.0	70.2	70.3	70.7	71.1	72.6	73.4	<b>74.9</b>