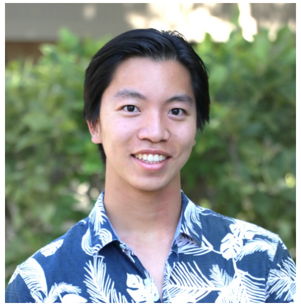
Connect, Not Collapse: Explaining Contrastive Learning for Unsupervised Domain Adaptation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Unsupervised domain adaptation (UDA)

Labeled source domain

Clock

Unsupervised domain adaptation (UDA)

Labeled source domain

Clock

Unlabeled target domain

?

Unsupervised domain adaptation (UDA)

Labeled source domain	Unlabeled target domain
	
Clock	*?*

Goal: high accuracy on target domain (without labels)

Classical approach for UDA

Labeled source domain

Source
representations

Unlabeled target domain

Target
representations

Classical approach for UDA

Labeled source domain

Source representations

High accuracy (given labels)

Unlabeled target domain

Target representations

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Match distributions

Classical approach for UDA

Motivated by theories such as $H\Delta H$ divergence (Ben-David et al 2010): want source and target reps to be “indistinguishable” to get good target accuracy

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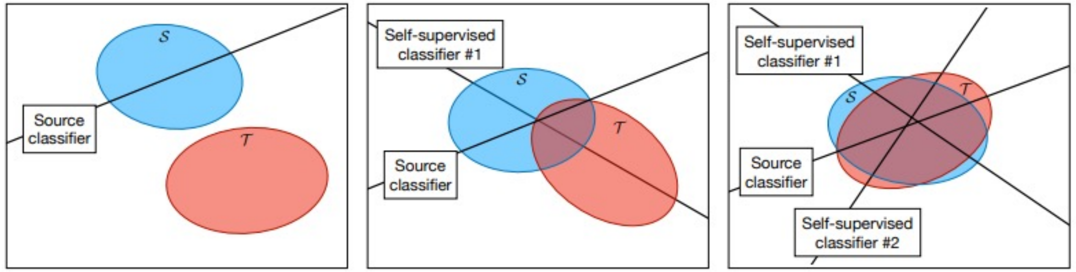
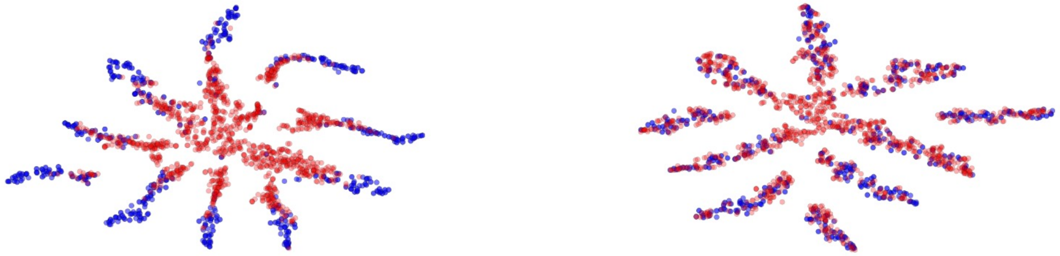


(a) Source classifier only (b) adding a self-supervised task (c) adding more tasks

UDA-SS (Sun et al. 2019)



(a) Non-adapted (b) Adapted

DANN (Ganin et al. 2016)

Pre-training for UDA

Step 1: pre-train on unlabeled data (combined source + target)

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Step 3: evaluate accuracy (target)

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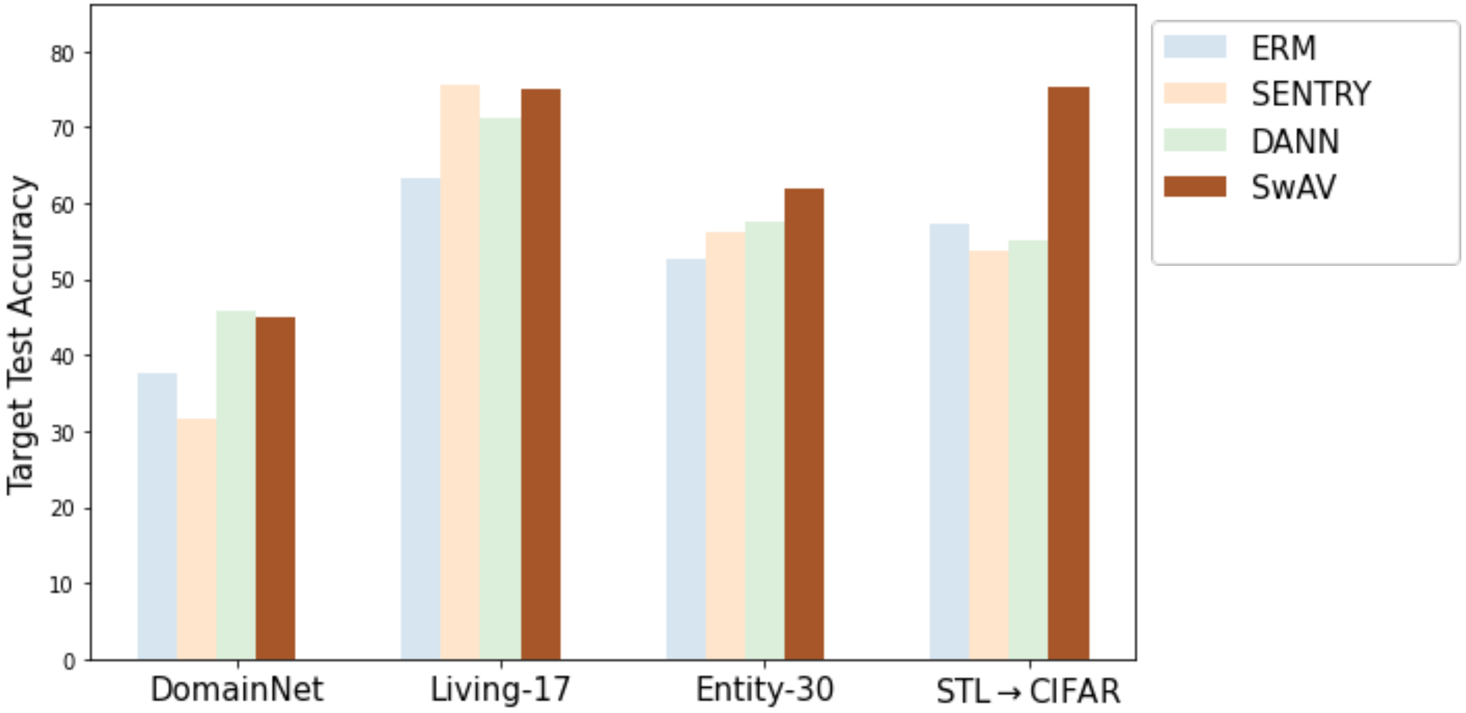
- Unsupervised representation learning for UDA inspired by e.g., Blitzer et al. 2007
  - Representations learned on diverse unlabeled data may relate domains, enabling transfer. But not typically used for deep models
- What about modern pre-training methods, such as contrastive learning (van den Oord et al. 2018, Chen et al. 2020, Caron et al. 2020)?

Contrastive pre-training for UDA

Contrastive pre-training (SwAV, Caron et al. 2020) is competitive with UDA methods (even when all methods use the same augmentations)



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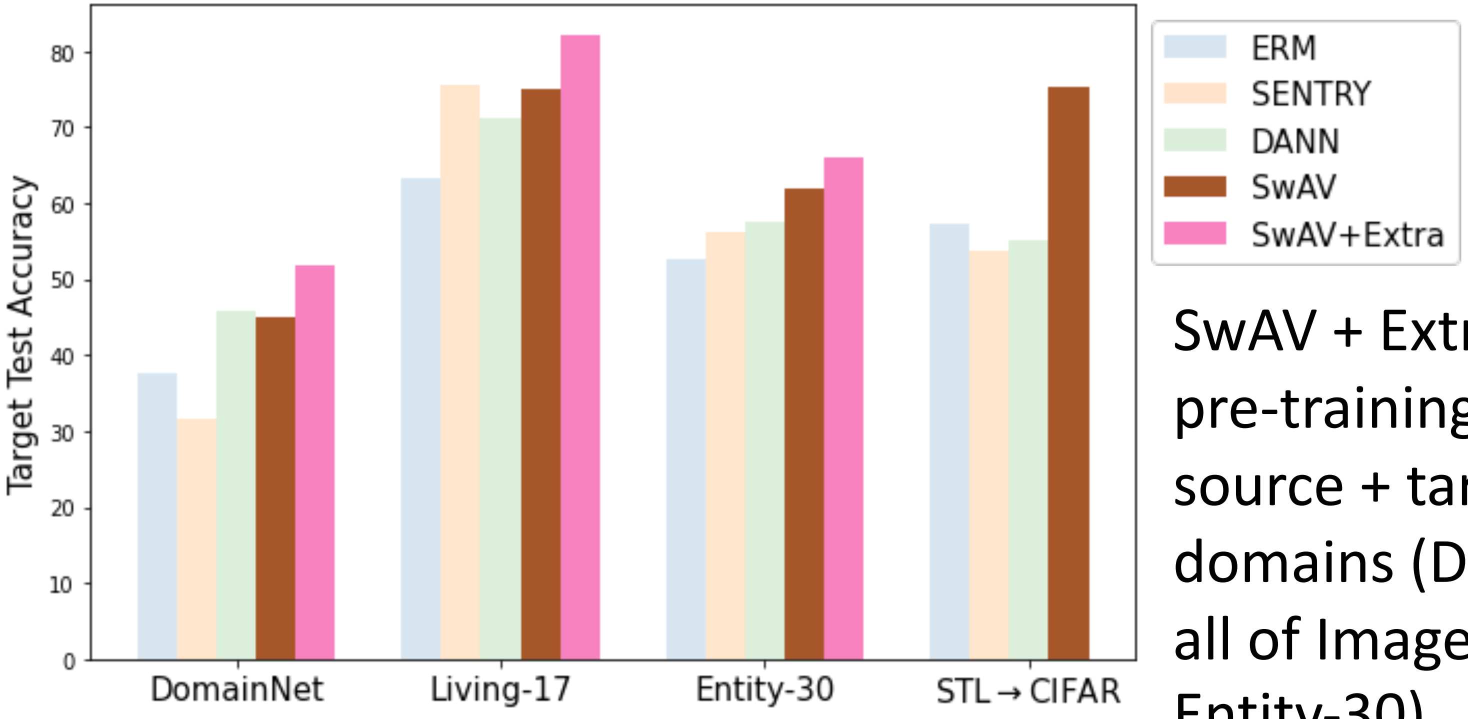

SwAV + Extra: unlabeled pre-training data beyond source + target = all 4 domains (DomainNet) or all of ImageNet (Living-17, Entity-30)

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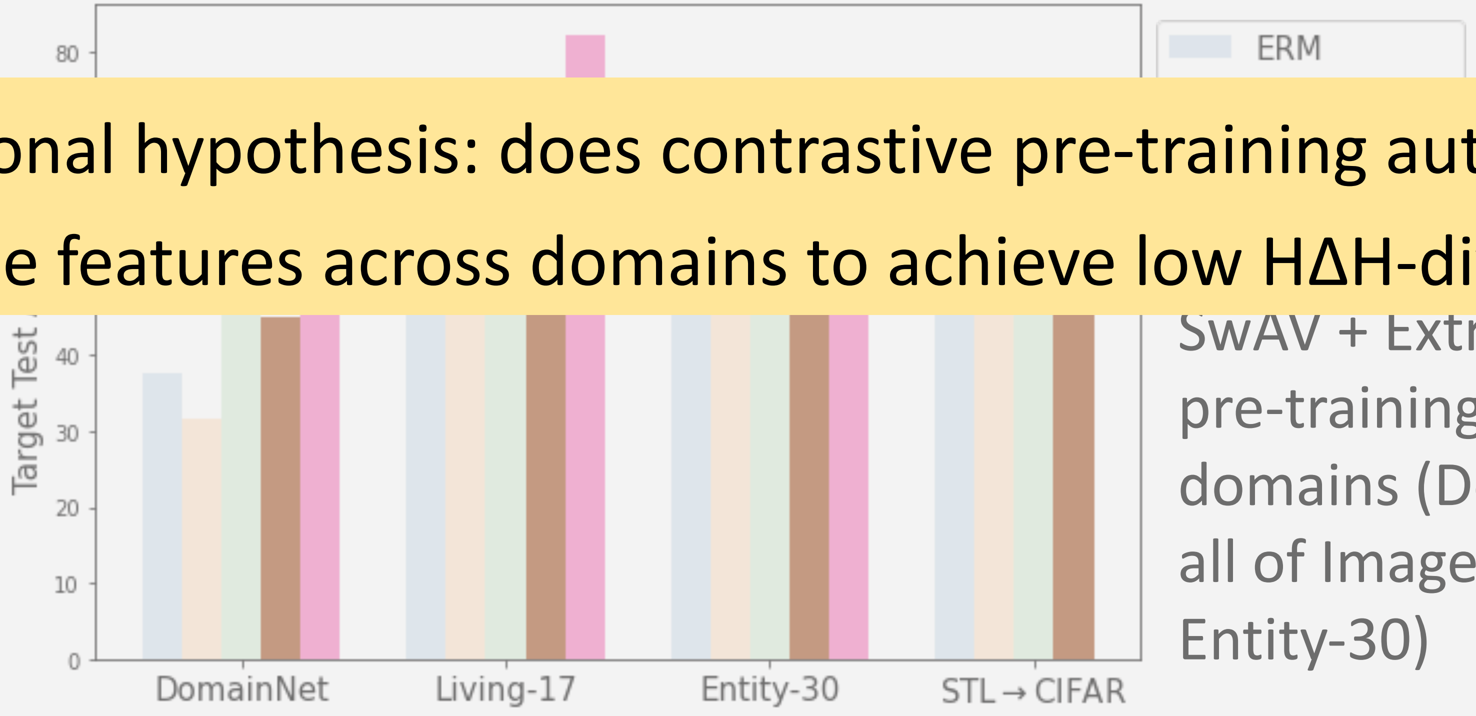

Conventional hypothesis: does contrastive pre-training automatically merge the features across domains to achieve low HΔH-divergence?

SwAV + Extra: unlabeled pre-training data = all 4 domains (DomainNet) or all of ImageNet (Living-17, Entity-30)

Contrastive pre-training doesn't bring domains together

Inspect DANN vs contrastive learning features: train discriminator between domains or between classes

Domain 1 (Sketch)

Domain 2 (Real)

Class 1 (Butterfly)

Class 2 (Clock)

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Domain 1 (Sketch)

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Class 1
(Butterfly)

Between classes
DANN: 6% err
Contrastive: 7% err

Class 2
(Clock)

Between domains
DANN: 14% err
Contrastive: 8% err

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Pre-training does not produce domain invariant features,
and domains are about as "far apart" as classes!

Contrastive pre-training for UDA

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Why do these features still generalize to the target without domain invariance?

Outline

- Setup: augmentation graph
- Intuitions and theoretical results
  - Main intuitions (toy example)
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  - map augmentations of different inputs to different features

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Domain 1 (Sketch) Domain 2 (Real)

Class 1
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Class 2
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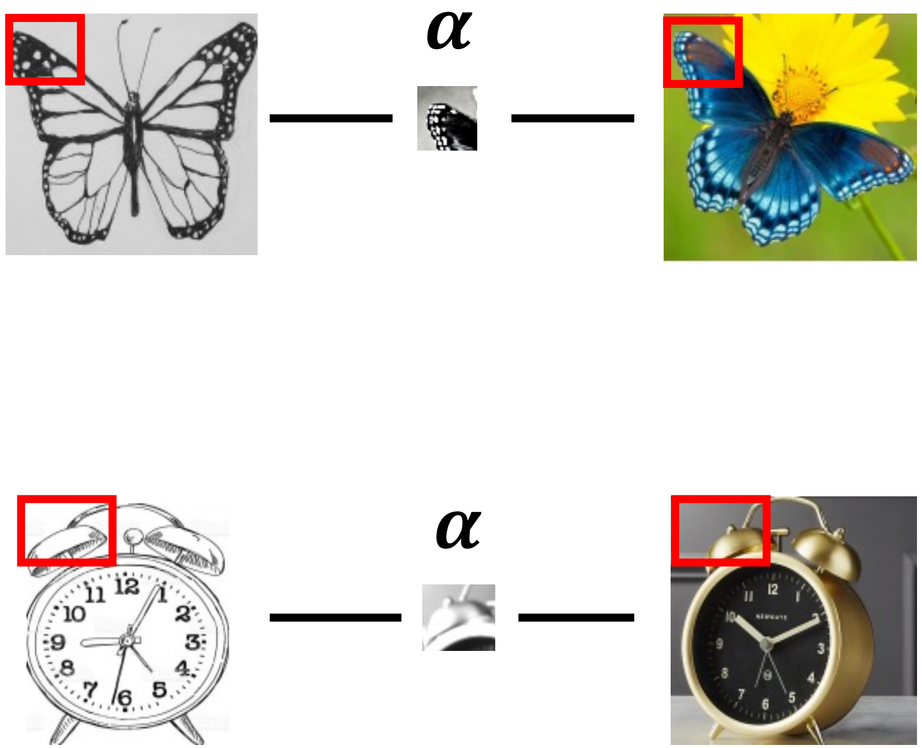

α: probability that augmentations of images coincide

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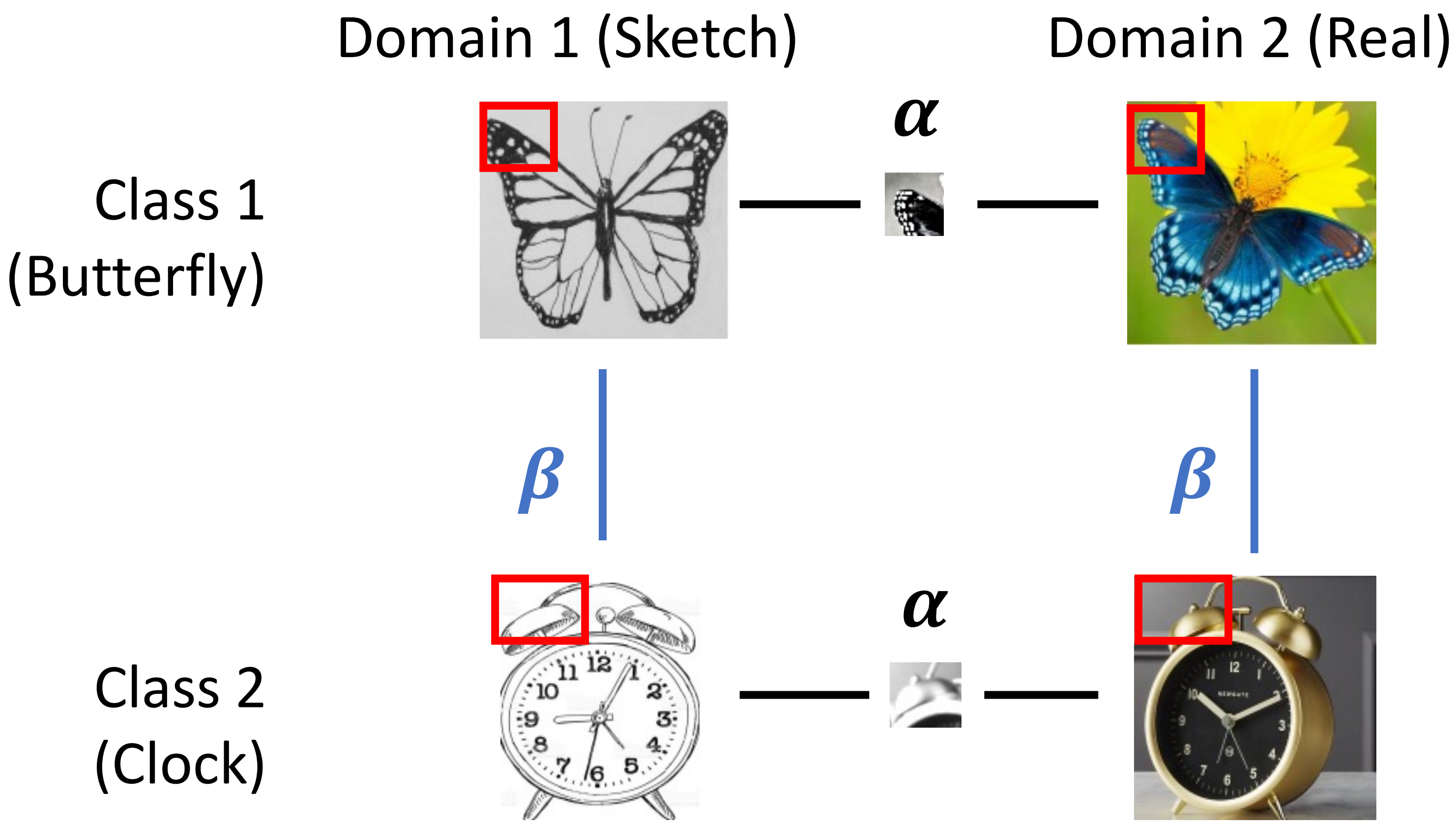

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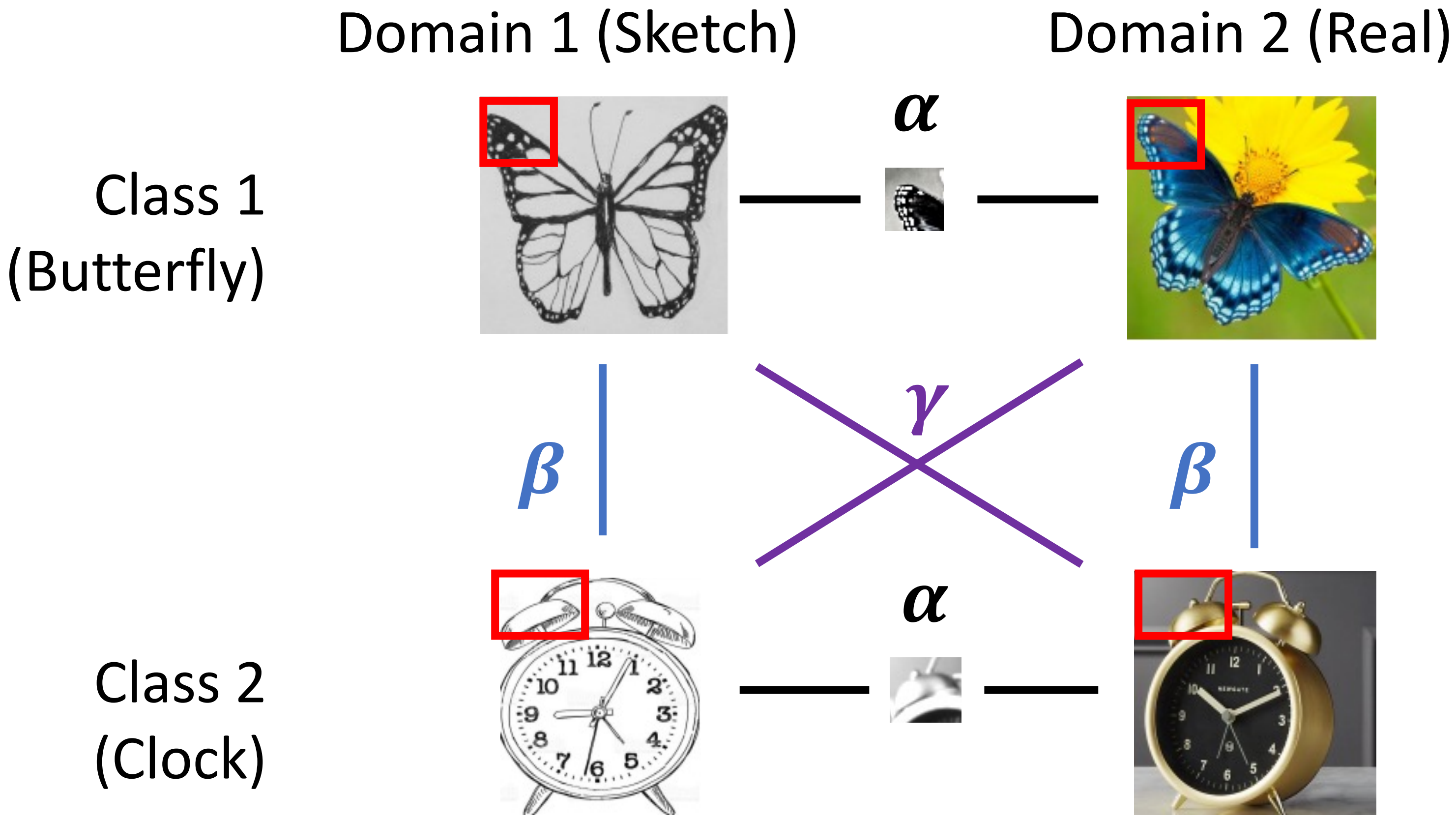

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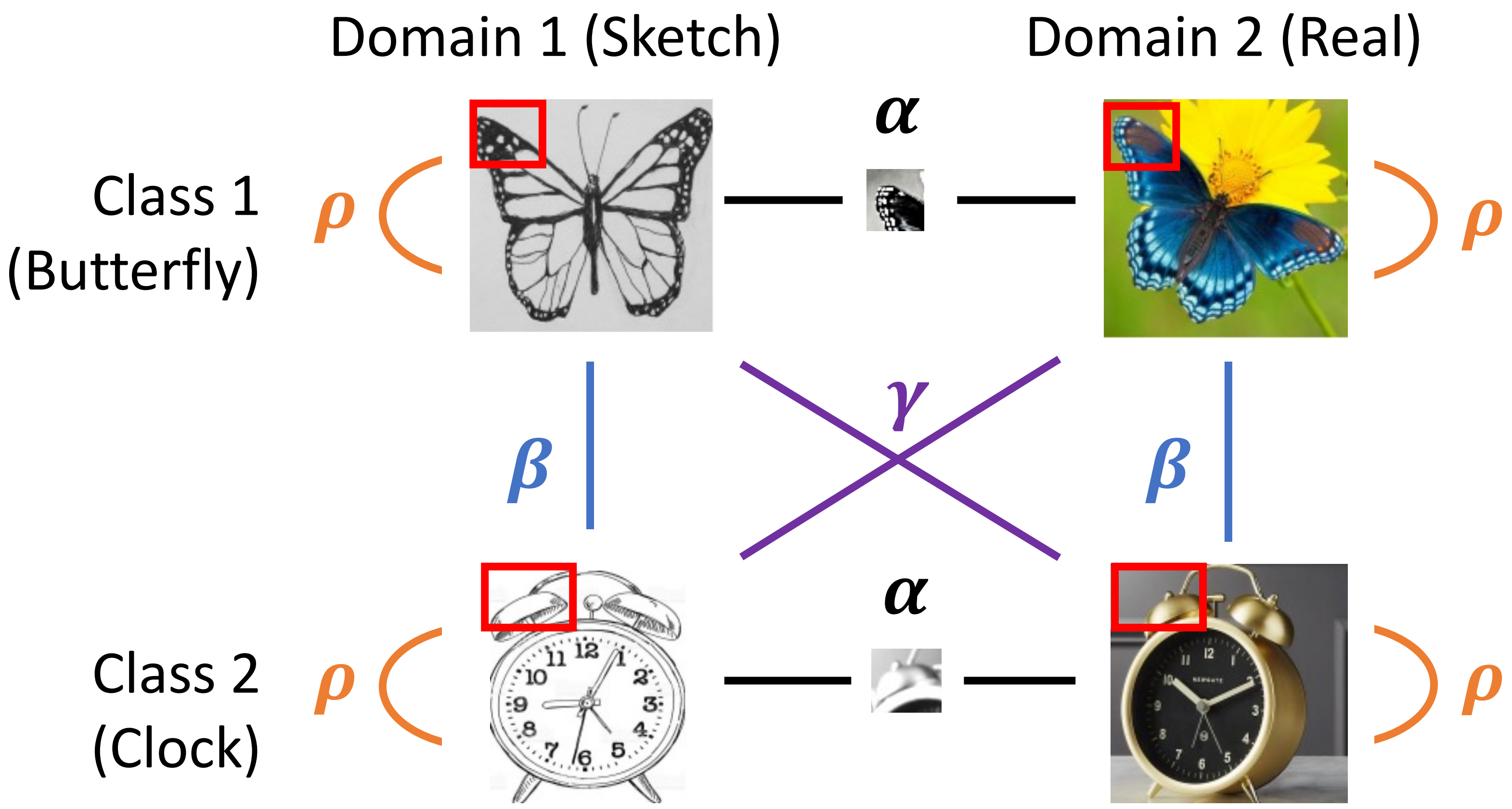

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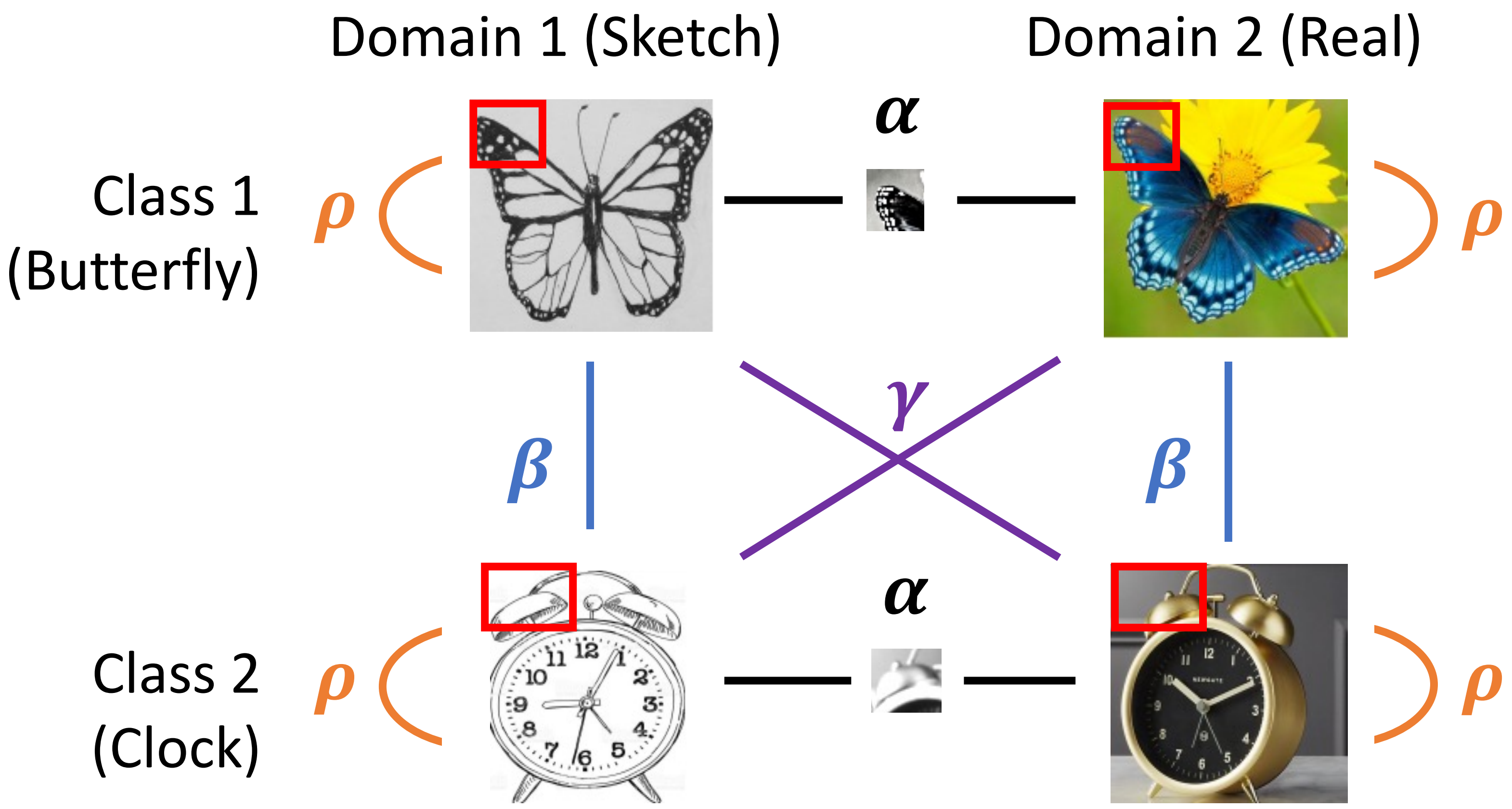
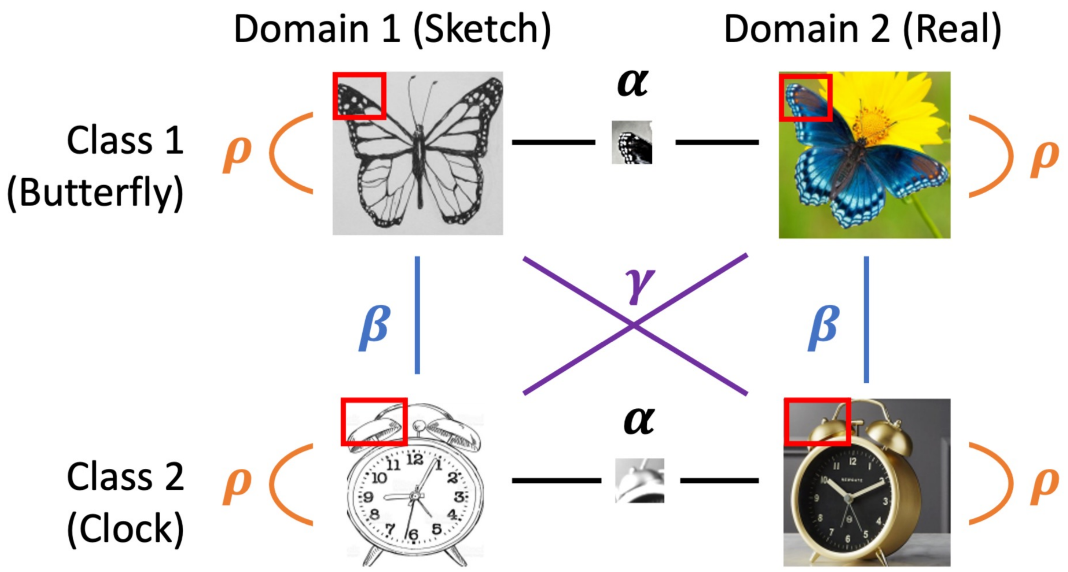


Magnitudes of connectivity parameters ρ, α, β, and $\gamma \approx$ similarity of augmentations

Setup: augmentation graph



	Sketch clock	Sketch butterfly	Real clock	Real butterfly
Sketch clock	ρ	β	α	γ
Sketch butterfly	β	ρ	γ	α
Real clock	α	γ	ρ	β
Real butterfly	γ	α	β	ρ

Can express augmentation graph using adjacency matrix A

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- We learn $\widehat{f} : X \to R^k$ that minimizes the spectral contrastive loss (HaoChen et al. 2021):

$$\mathcal{L}_{\text{pretrain}}(f) = -2 \cdot \mathbb{E}_{(x,x^+)\sim S_+}\left[f(x)^\top f(x^+)\right] + \mathbb{E}_{x,x'\sim P_U}\left[\left(f(x)^\top f(x')\right)^2\right]$$

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- In our toy example, we can compute $\widehat{f}$ exactly and then visualize the (learned) representations

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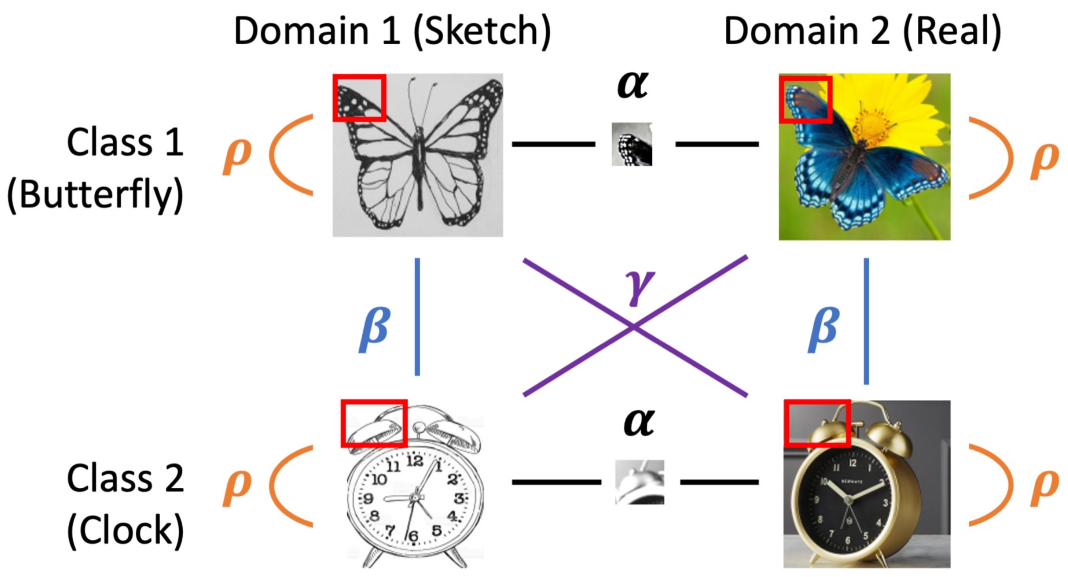

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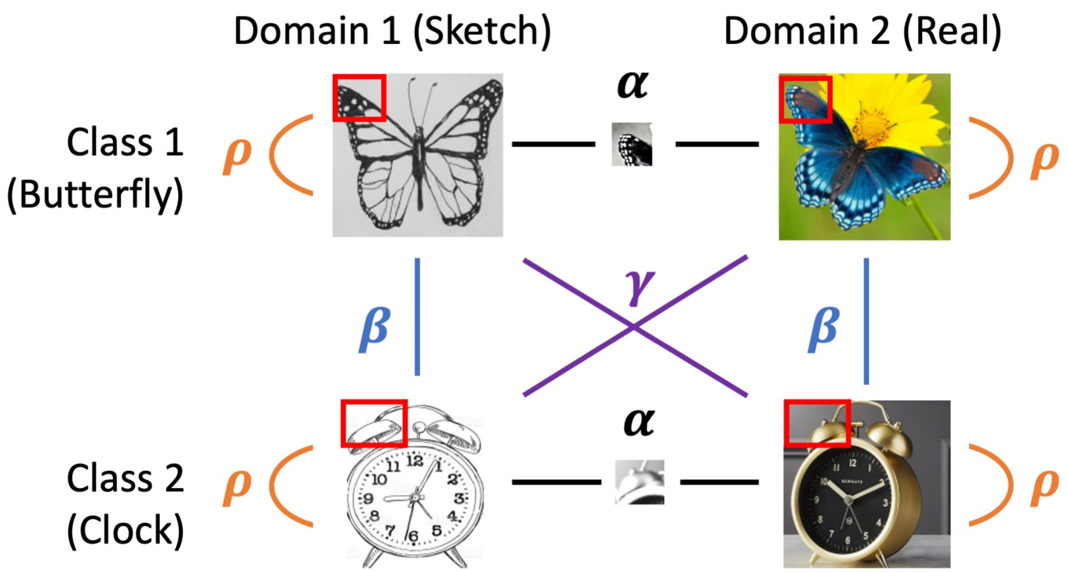

$$\hat{F} = \begin{bmatrix} \longleftarrow & \hat{f}\,(\text{sketch clock}) & \longrightarrow \\ \longleftarrow & \hat{f}\,(\text{sketch butterfly}) & \longrightarrow \\ \longleftarrow & \hat{f}\,(\text{real clock}) & \longrightarrow \\ \longleftarrow & \hat{f}\,(\text{real butterfly}) & \longrightarrow \end{bmatrix}$$

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$\Longrightarrow$ connectivity parameters control pre-trained features $\hat{F}$

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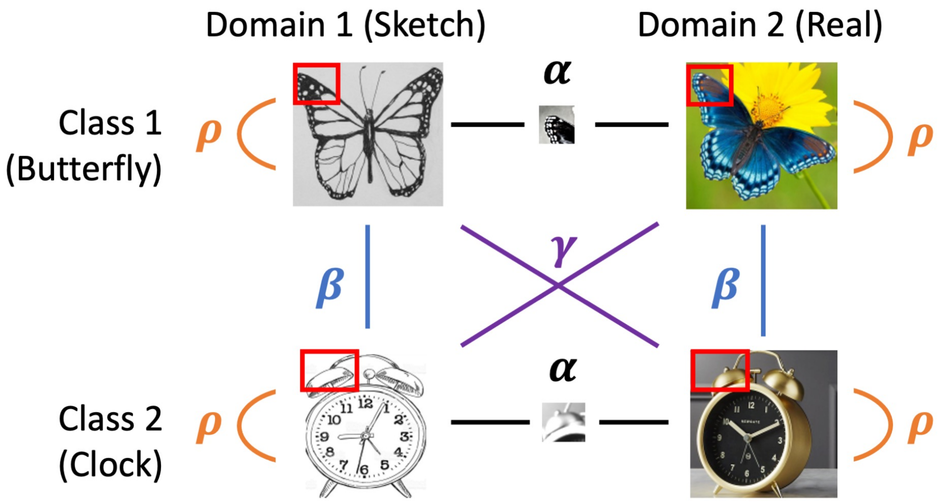
If $\mathbf{min}(\boldsymbol{\alpha}, \boldsymbol{\beta}) > \boldsymbol{\gamma}$ (and self-loop ρ is the largest):



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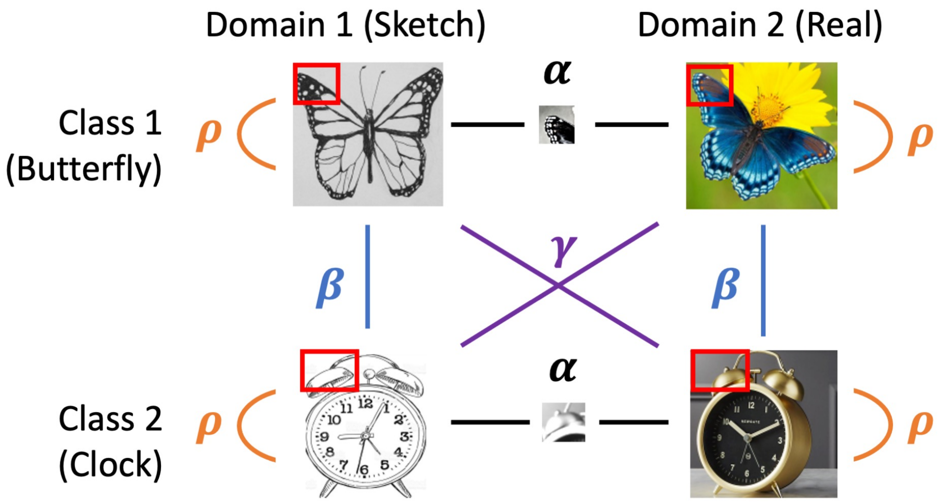

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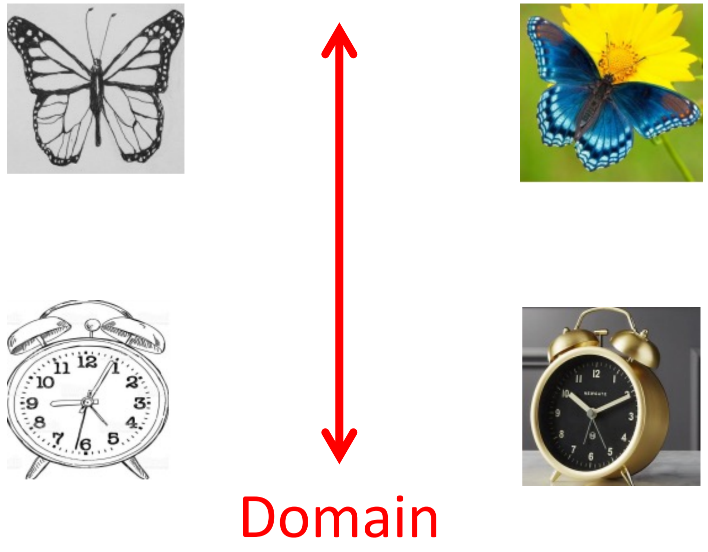

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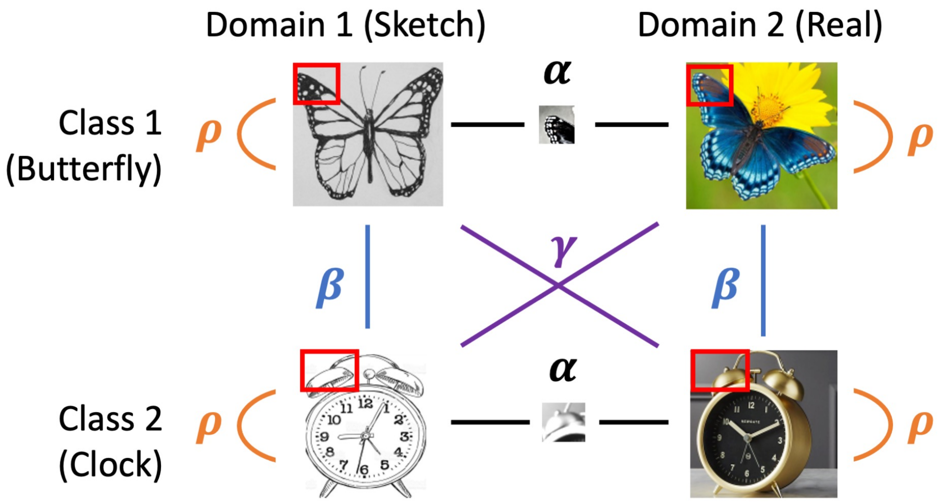

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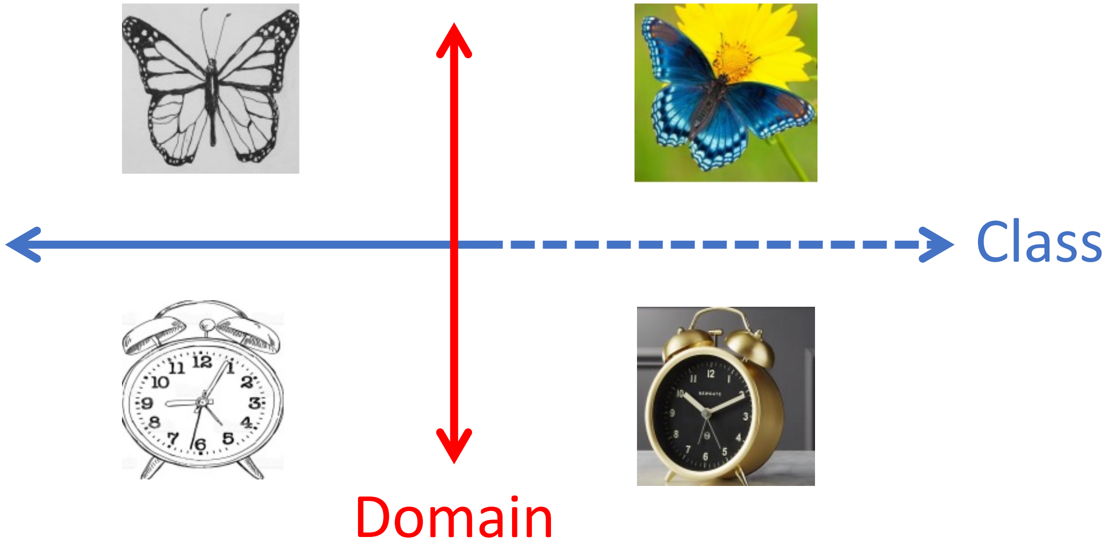

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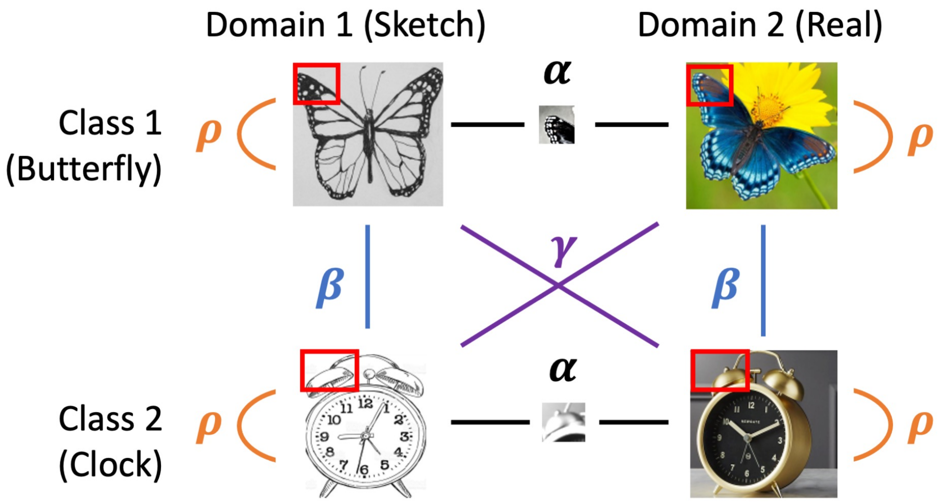

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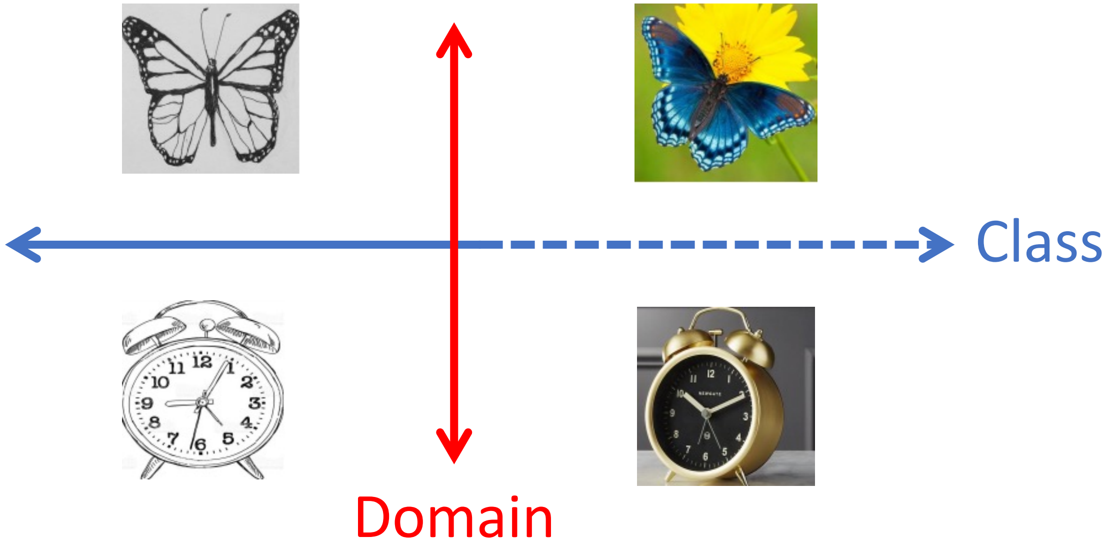

Key condition for transfer: augmentations are more likely to change **only domain** (α) or **only class** (β) than **both domain and class** (γ)

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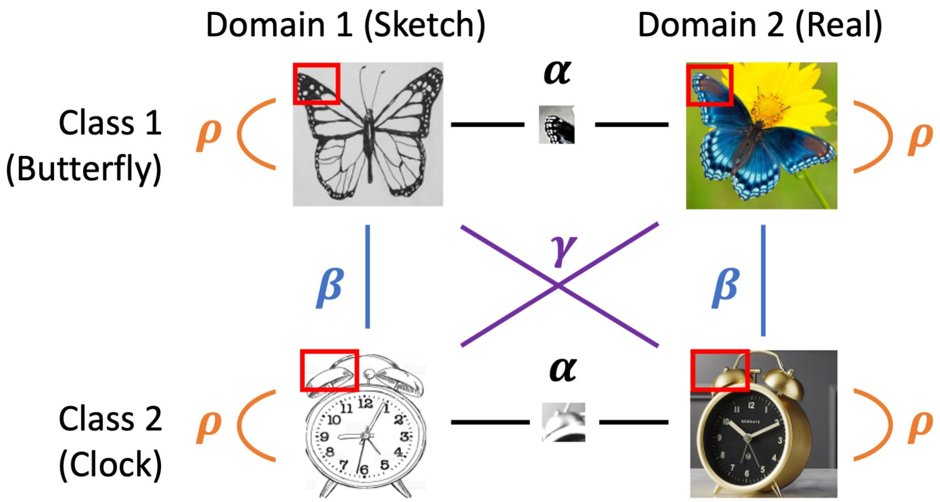

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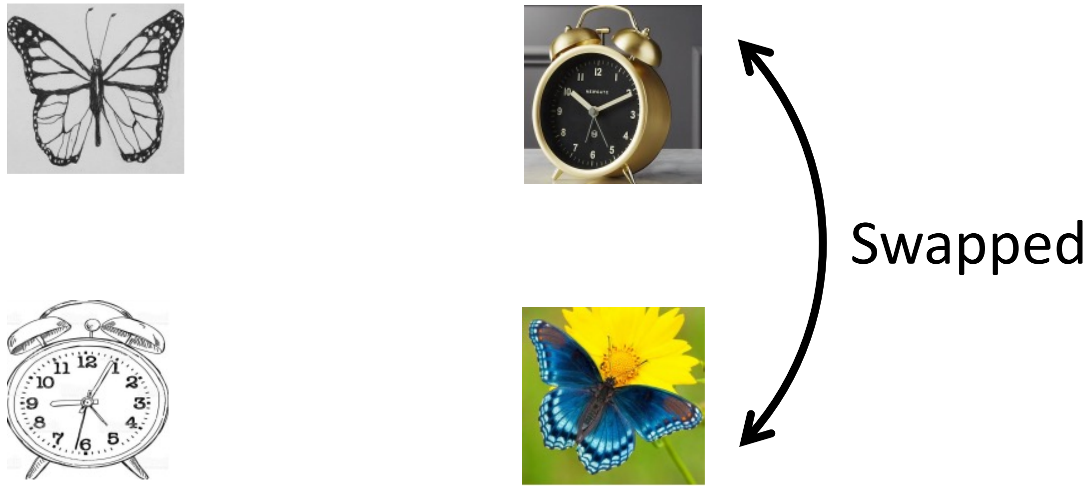

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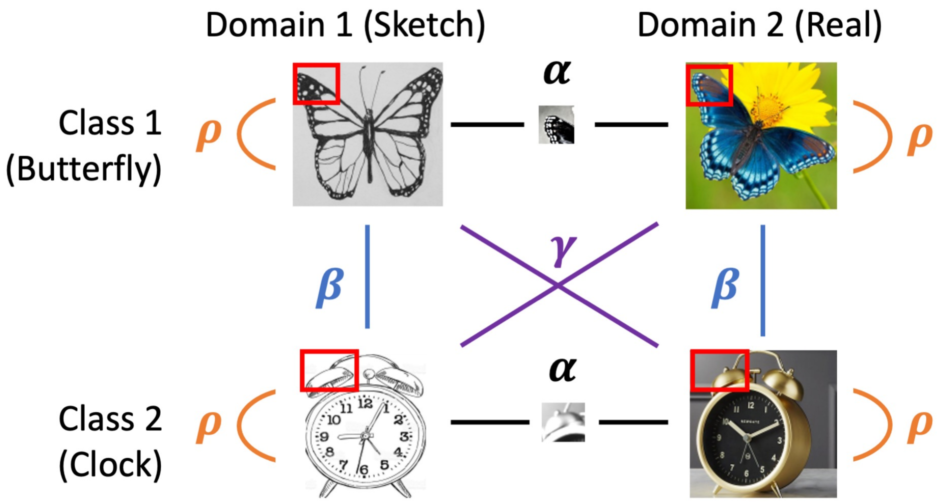

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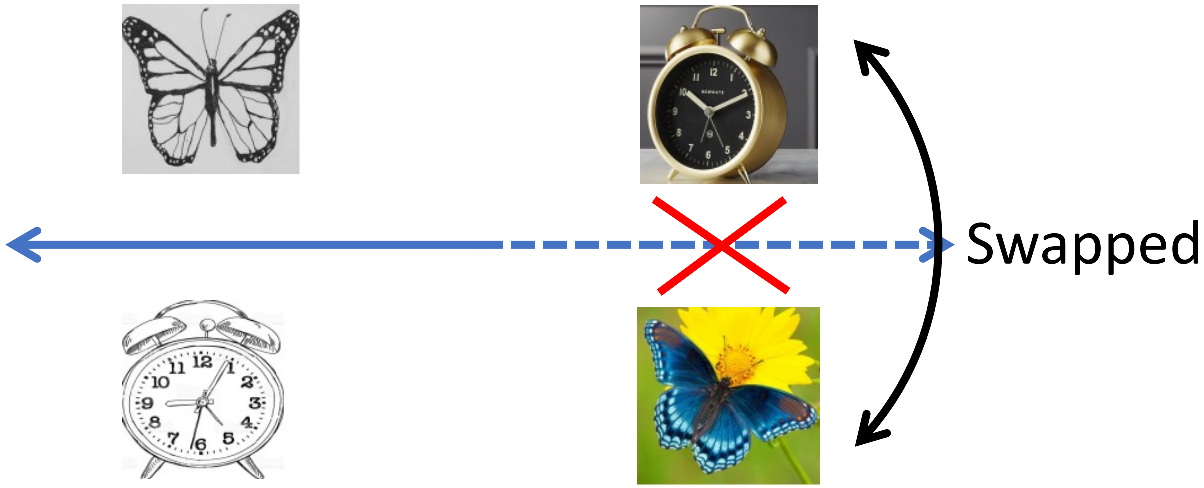

If the condition is violated, the target features can be "swapped" so that a source-trained linear classifier fails to generalize

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- Follow-up work generalizes beyond random graph models: HaoChen et al. 2022

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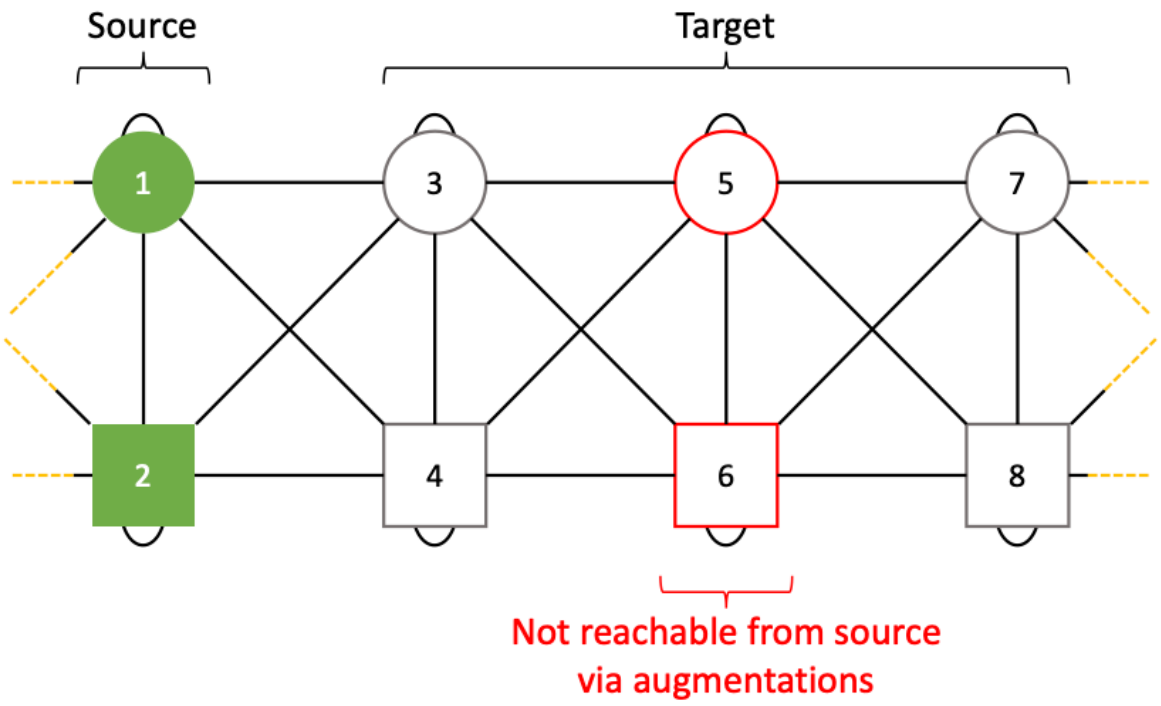

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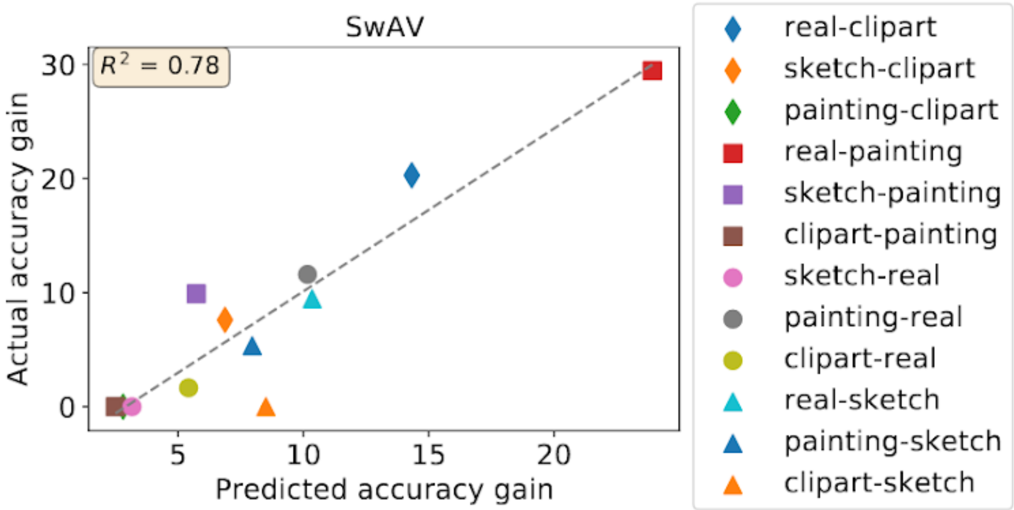
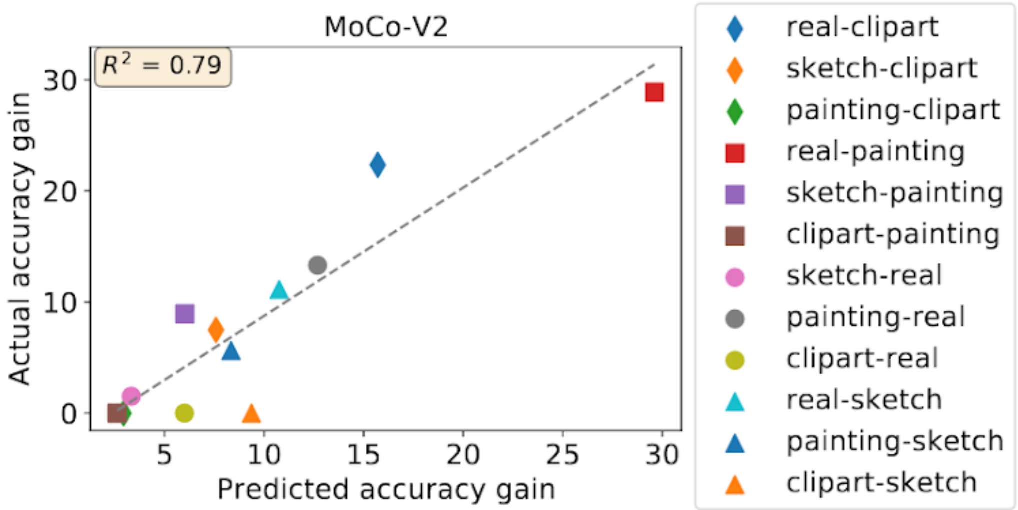
$$\text{target accuracy} \approx (\alpha/\gamma)^{w_1} \cdot (\beta/\gamma)^{w_2}$$

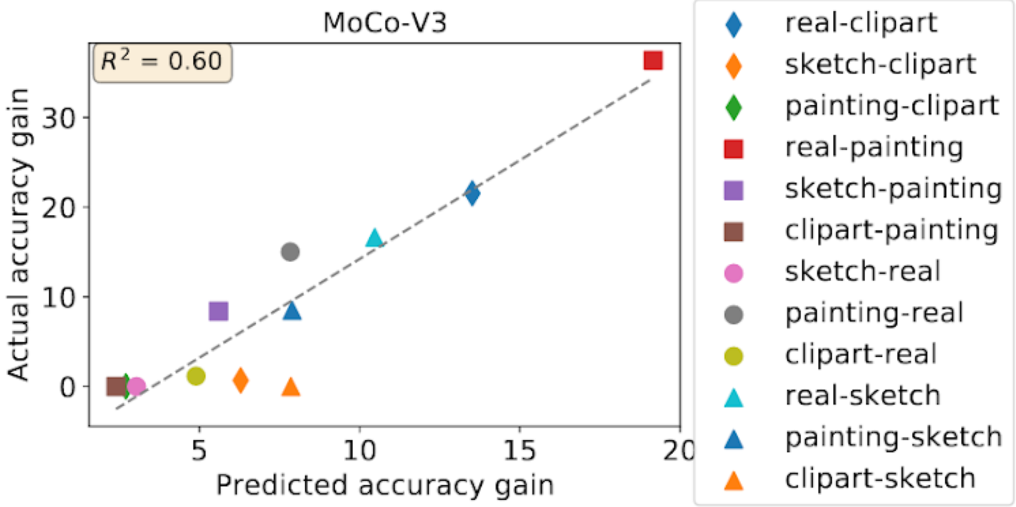
- Estimate w_1, w_2 by fitting a linear function in log space and determine quality of fit compared to a control

Predicting target accuracy (contrastive methods)

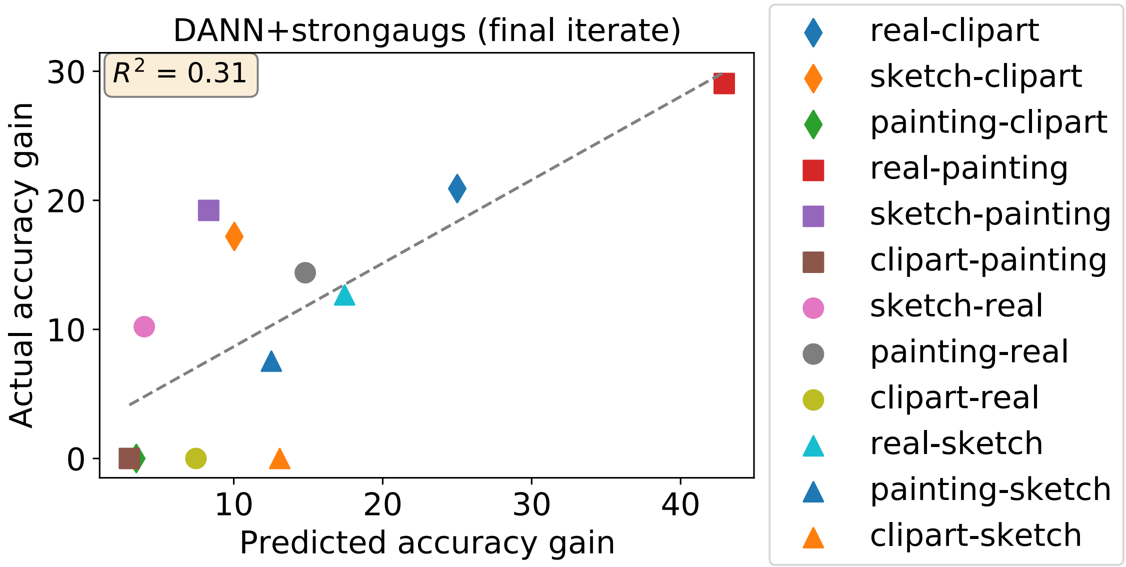


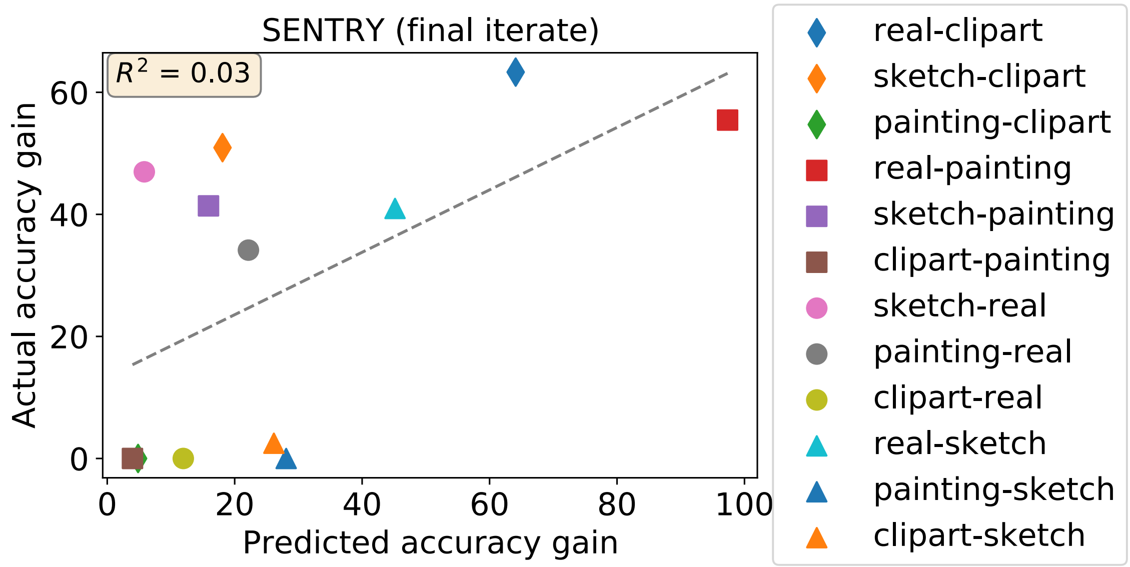


Method	R^2
SwAV	0.78
MoCo-V2	0.79
MoCo-V3	0.60



Predicting target accuracy (controls)





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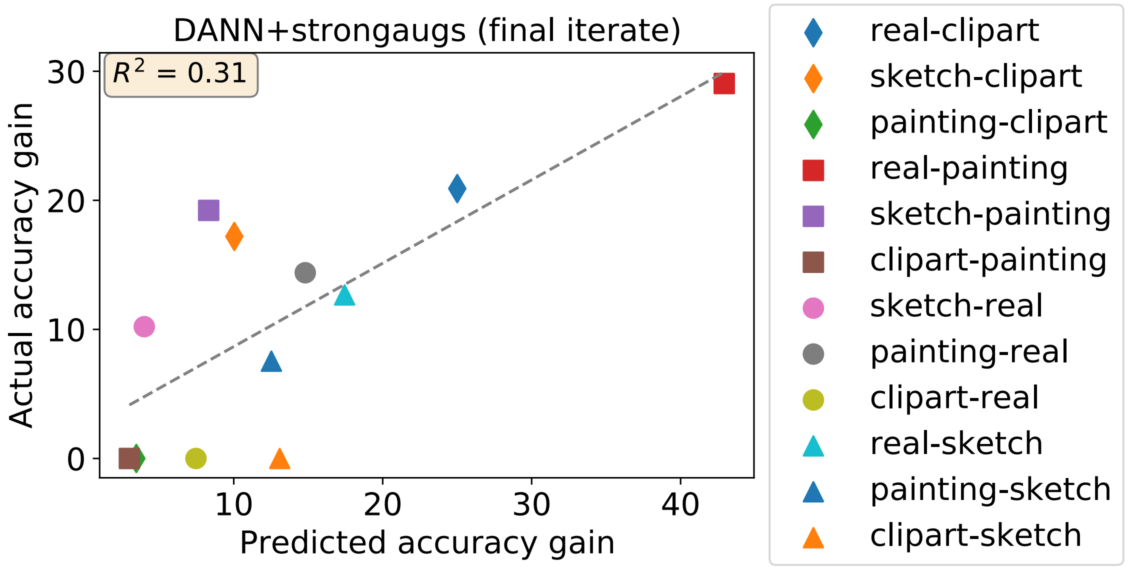

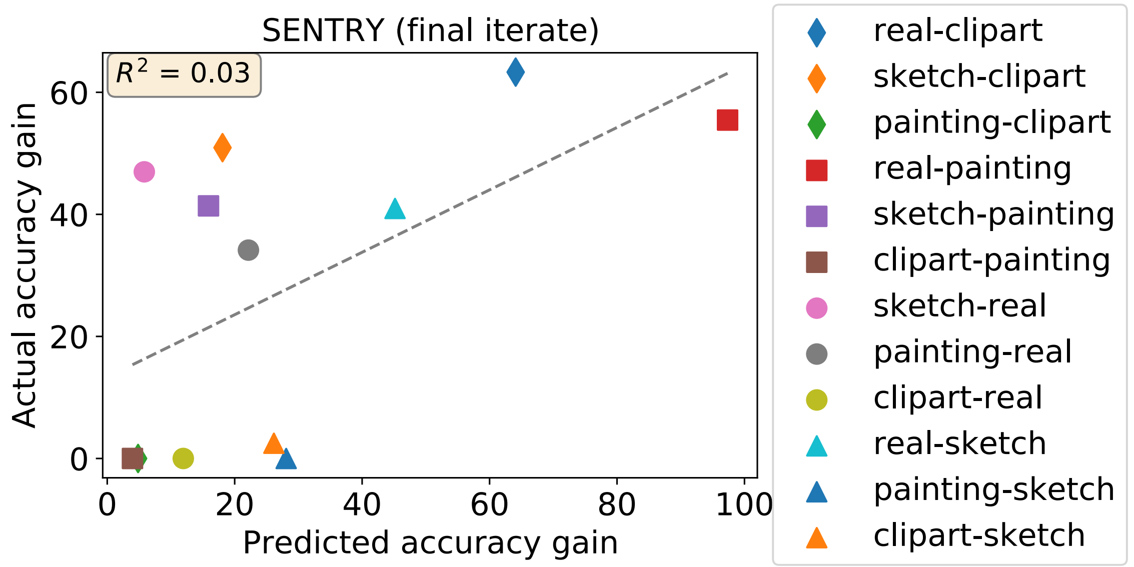

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DANN	0.31
SENTRY	0.03

Lower quality of fit for non-contrastive methods: DANN and SENTRY

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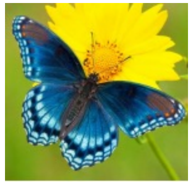

	f_{src} vs. f_{tgt}	f_{src} vs. f_{dom}	f_{tgt} vs. f_{dom}
Living-17	0.397	0.013	0.016
DomainNet	0.187	0.018	0.018


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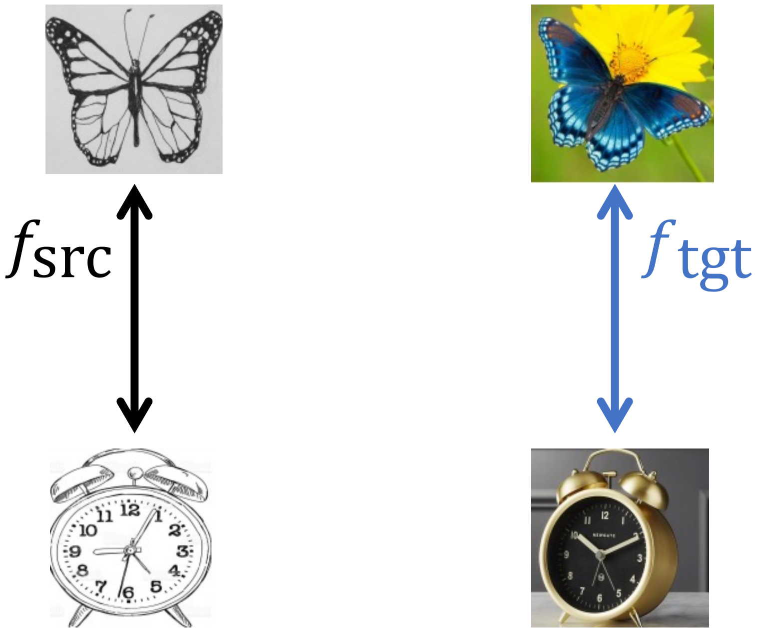

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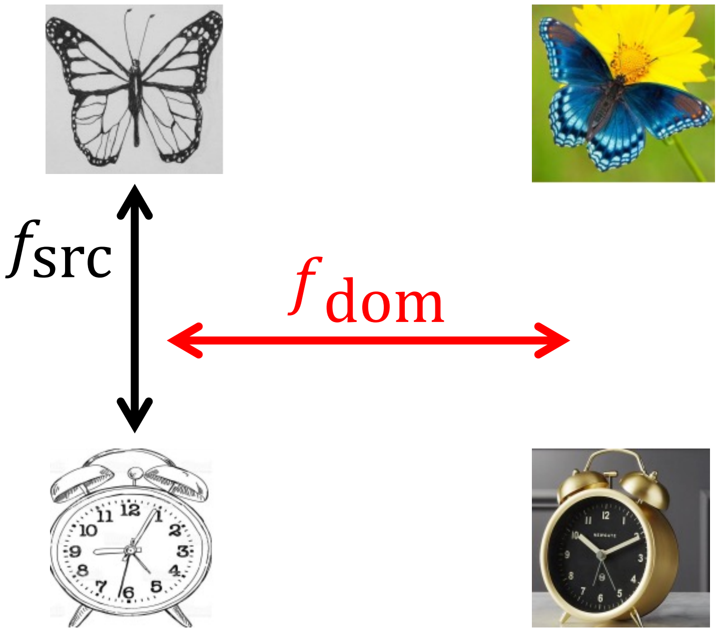

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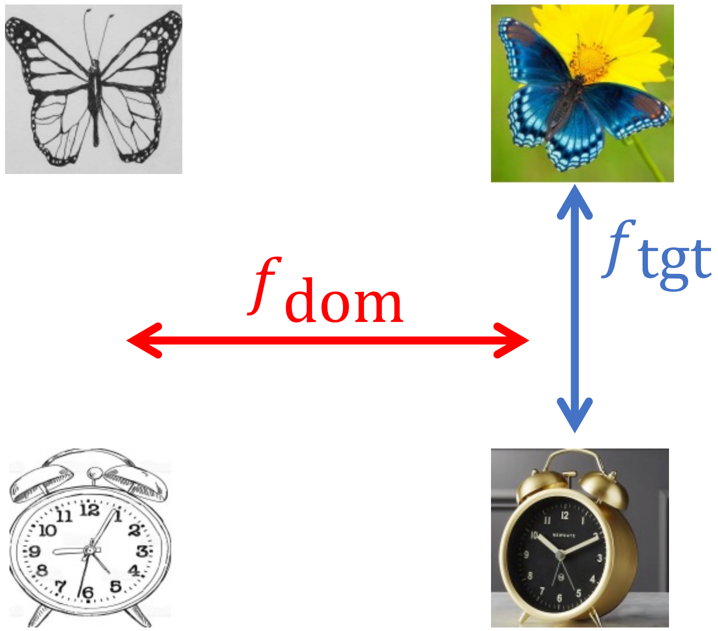
Living-17	0.397	0.013	0.016
DomainNet	0.187	0.018	0.018

Orthogonal

Class and domain are disentangled

- We train a linear probe for class and domain information in the contrastive features, finding that class and domain classifiers have low cosine similarity



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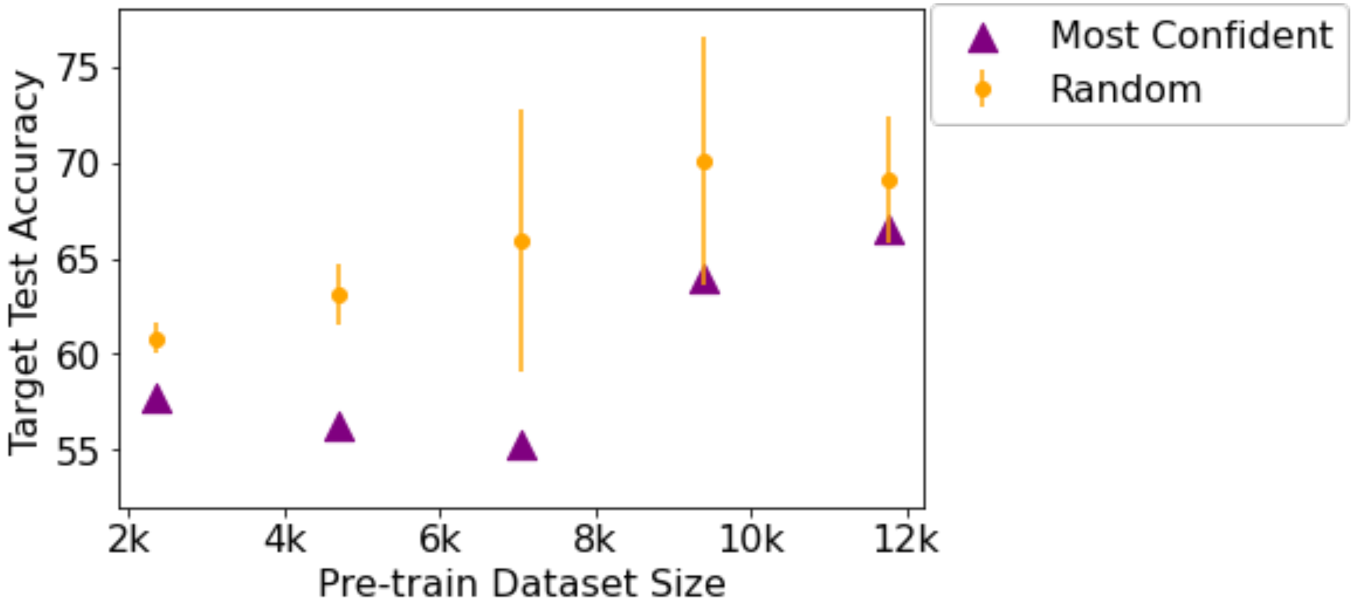

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	ERM	SwAV (S)	SwAV (T)	**SwAV (S+T)**
Living-17	63.29	62.71	70.41	**75.12**
Entity-30	52.52	52.33	60.33	**62.03**

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- Instead, disentangles class and domain information, enabling transfer
  - Consequence of the structure of connections between domains and classes via data augmentations