CLAP: Isolating Content from Style through Contrastive Learning with Augmented Prompts

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Motivation

CLIP - Trained on massive image-text data with a symmetric InfoNCE loss.

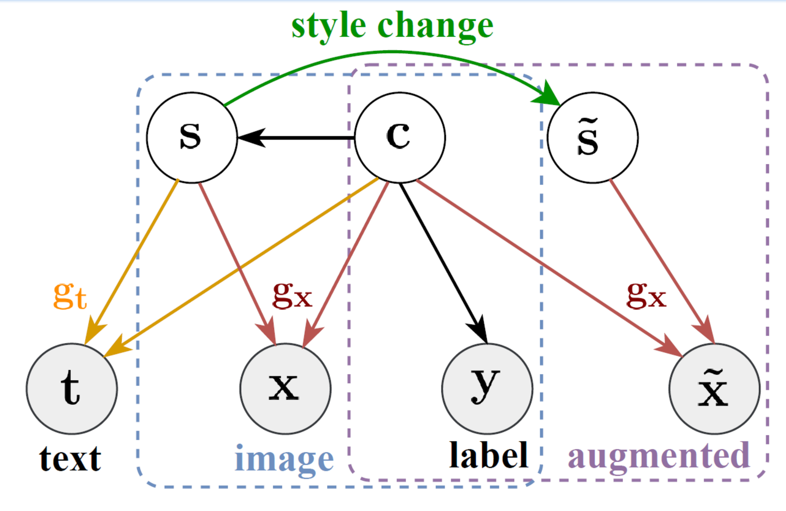
Pros	Cons
✓ Mitigated modality gap	• Zero-shot sensitive to prompts
✓ High zero-shot performance	• Few-shot performance degrades
✓ Great generalization ability	• Vulnerable to adversarial attacks

Intuition - There exists spurious correlations in CLIP features, i.e., style-related information is erroneously used to predict class labels.

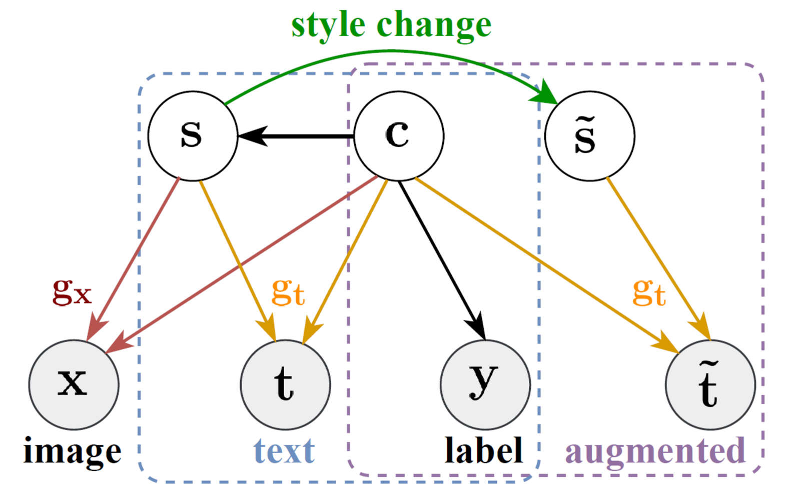
Contribution

- We propose a contrastive learning method to disentangle content and style in pretrained CLIP-like models.
- Our disentangled network, trained on either the image or text encoder, can be seamlessly applied to both modalities.
- Leveraging the high semantic structure of text data, we introduce **CLAP** (Contrastive Learning with Augmented Prompts) to isolate content features within the pre-trained CLIP feature space.

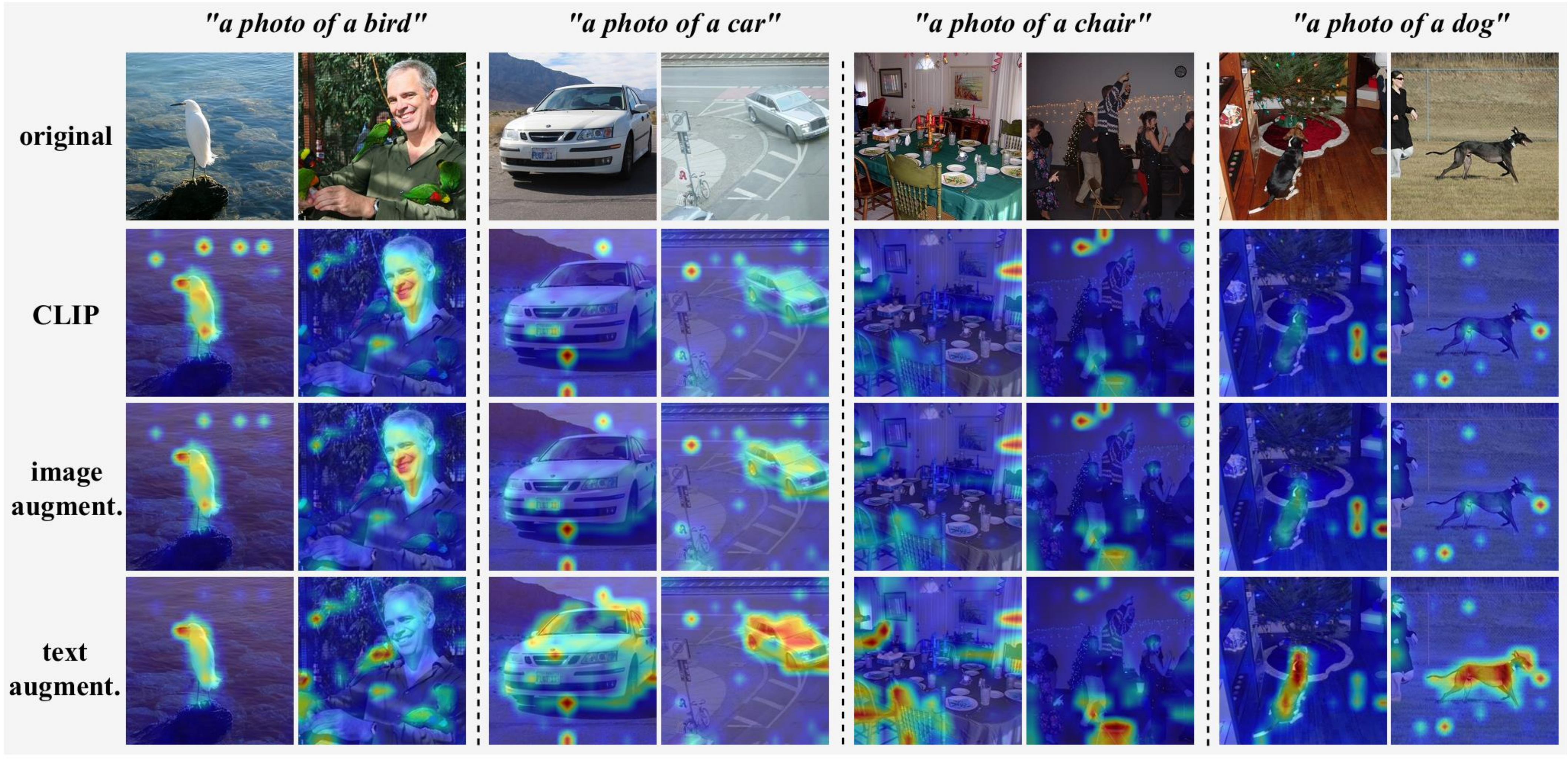
Causal Generative Models of Vision-Language Data



(a) Image augmentation



(b) Text augmentation

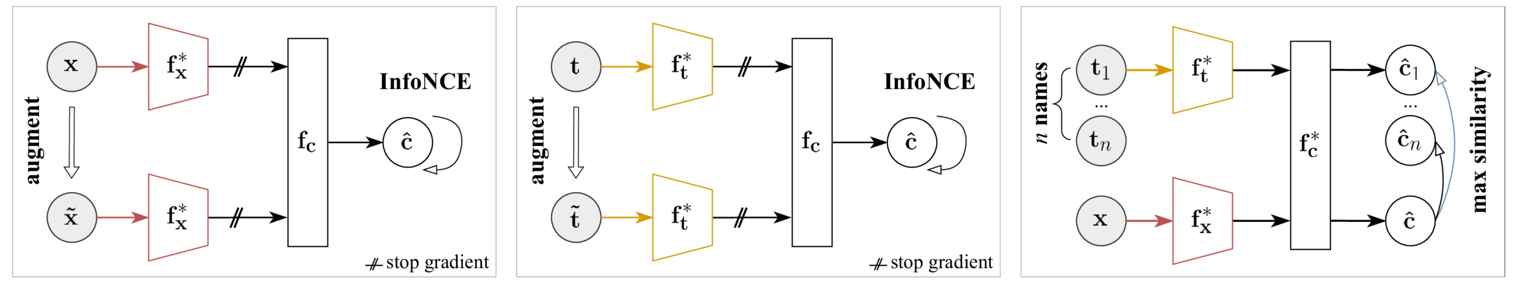


CAM Visualization: Comparative visualization of features from CLIP, Image augmentation (Im.Aug), and Text augmentation (CLAP) for zero-shot inference.

Insight – Image $\mathbf{x}$ and text $\mathbf{t}$, derived from a unified latent space with content $\mathbf{c}$ and style $\mathbf{s}$, follow distinct deterministic processes, $\mathbf{g}_x$ and $\mathbf{g}_t$. The class label $\mathbf{y}$ is determined solely by the latent content. (a) Soft interventions on style variables generate augmented images $\tilde{\mathbf{x}}$. (b) Similar interventions produce augmented text $\tilde{\mathbf{t}}$ due to the shared latent space.

Isolating Content through Data Augmentation

❑ Framework



(a) Image augmentation (Im.Aug) (b)Text augmentation (CLAP) (c)Zero-shot inference

Innovation - Contrastive learning with data augmentation in one modality benefits both, with text data being more amendable for style changes due to its semantic structure. The trained adapting network can be seamlessly applied in both modality for zero-shot inference.

❑ Contrastive Learning with Augmented Images (Im.Aug)

Template Prompts *"an [art style] [image type] of an [object size] [object color] [class]"*

Text-to-image diffusion model

object color	object size	image type	art style
yellow, green, black, blue, multicolored, orange, red, white, brown, purple	large, small, normal sized	painting, cartoon, infograph, sketch, photograph, clipart, mosaic art, sculpture	realistic, impressionistic

Synthetic Images

a realistic painting of a large blue aircraft carrier; an impressionistic mosaic art of a small black backpack; a realistic photograph of a large black car; a realistic sketch of a large black mug; an impressionistic painting of a normal sized green train

Image Augmentation Random cropping + color distortion

❑ Contrastive Learning with Augmented Prompts (CLAP)

Template Prompts *"an [art style] [image type] of an [object size] [object color] [class]"*

Text Augmentation Randomly apply the combination of these techniques:

Original	OSD Object Size Deletion	OCD Object Color Deletion	ITD Image Type Deletion	ASD Art Style Deletion	SPO Swapping Prompt Order
a realistic painting of a large red car	a realistic painting of a red car	a realistic painting of a large car	a realistic of a large red car	a painting of a large red car	a large red car in a realistic painting

Experimental Results

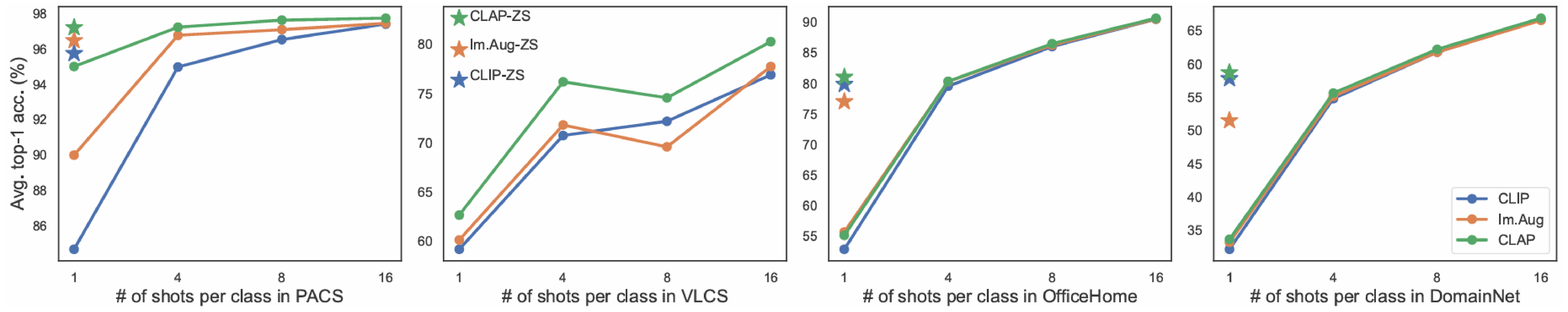
❑ Zero-shot performance

Prompt	Method	PACS	VLCS	Off.Home	Dom.Net	Overall
		Zero-shot performance, avg. top-1 acc. (%) (↑)				
ZS(C)	CLIP	95.7	76.4	79.8	57.8	77.4
	Im.Aug	96.5	79.5	77.0	51.5	76.1
	CLAP	**97.2**	**82.6**	**81.0**	**58.7**	**79.9**
ZS(CP)	CLIP	95.2	82.0	79.5	57.0	78.4
	Im.Aug	96.3	82.9	75.8	50.7	76.4
	CLAP	**97.3**	**83.4**	**80.5**	**58.0**	**79.8**
ZS(PC)	CLIP	96.1	82.4	82.5	57.7	79.7
	Im.Aug	96.5	83.0	78.6	51.6	77.4
	CLAP	**97.2**	**83.4**	**83.0**	**59.0**	**80.6**
ZS(NC)	CLIP	90.8	68.3	71.5	51.0	70.4
	Im.Aug	94.8	73.1	67.5	44.0	69.9
	CLAP	**97.2**	**81.0**	**73.5**	**52.6**	**76.1**

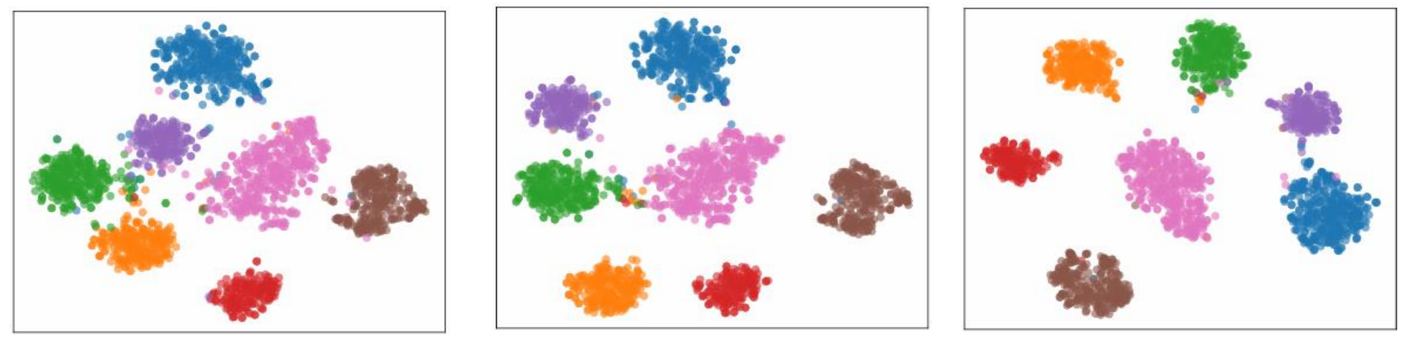
Metric	Method	PACS	VLCS	Off.Home	Dom.Net	Overall
		Performance variance, avg. top-1 acc. (%) (↓)				
R	CLIP	0.9	6.1	3.1	**0.8**	2.7
	Im.Aug	**0.1**	3.6	2.8	0.9	1.9
	CLAP	**0.1**	**0.8**	**2.5**	1.0	**1.1**
δ	CLIP	0.4	2.8	1.4	**0.4**	1.2
	Im.Aug	0.1	1.7	1.2	**0.4**	0.8
	CLAP	**0.0**	**0.4**	**1.1**	**0.4**	**0.5**
$\Delta_{(NC)}$	CLIP	4.9	8.1	8.3	6.8	7.0
	Im.Aug	1.6	6.4	9.5	7.5	6.3
	CLAP	**0.0**	**1.6**	**7.5**	**6.1**	**3.8**

Inference prompts: **ZS(C)** – "[class]" **ZS(CP)** – "a [class] in a photo" **ZS(PC)** – "a photo of a [class]" **ZS(NC)** – "[Gaussian noise][class]"

❑ Few-shot performance



❑ Qualitative analysis with t-SNE visualization



t-SNE comparison of CLIP, Im.Aug, and CLAP features (from left to right) on the PACS dataset, Art Painting domain

❑ Adversarial robustness

Setting	Method	FGSM PACS	FGSM VLCS	FGSM O.H.	FGSM D.N.	PGD-20 PACS	PGD-20 VLCS	PGD-20 O.H.	PGD-20 D.N.	CW-20 PACS	CW-20 VLCS	CW-20 O.H.	CW-20 D.N.	Avg.
		Avg. top-1 acc. (%) under adversarial attacks(↑)												
ZS(C)	CLIP	86.8	65.6	57.9	22.5	29.1	2.0	10.1	10.7	27.4	1.5	7.4	7.6	29.2
	Im.Aug	88.0	69.6	55.1	37.9	**31.3**	2.1	10.4	9.0	29.4	1.7	7.0	5.8	31.1
	CLAP	**88.7**	**71.9**	**58.5**	**44.2**	30.8	**3.2**	**10.6**	**11.2**	**29.8**	**2.3**	**8.1**	**8.0**	**32.7**
1-shot	CLIP	66.7	45.2	34.3	22.5	34.8	16.0	5.6	11.3	18.9	0.7	4.5	3.2	23.7
	Im.Aug	79.4	47.1	**37.1**	23.5	55.2	16.1	**8.5**	**12.5**	23.2	0.9	**5.1**	3.4	28.0
	CLAP	**89.6**	**52.2**	**37.1**	**23.9**	**73.4**	**21.2**	7.4	**12.5**	**27.0**	**1.1**	5.0	**3.5**	**31.9**

- CLAP successfully refines pretrained CLIP features by effectively isolating content from style, as demonstrated by improved zero-shot and few-shot performance, increased robustness against adversarial attacks, and enhanced qualitative visualizations.
- Exploring the more efficient data augmentation techniques, including the combination of augmentations from both modalities could be valuable, given their complementary strengths.

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