Improving Foundation Model Group Robustness with Auxiliary Sentence Embeddings

Anonymous authors
Paper under double-blind review

Abstract

This paper addresses the critical challenge of mitigating group-based biases in vision-language foundation models, a pressing issue for ensuring trustworthy AI deployment. We introduce DoubleCCA, a novel and computationally efficient framework that systematically enriches textual representations to enhance group robustness. Our key innovation is to leverage an auxiliary large sentence embedding model to capture diverse semantic perspectives, counteracting biased representations induced by limited training data. To this end, we propose a two-stage Canonical Correlation Analysis (DoubleCCA) technique: first, aligning augmented and original embeddings in a shared space; second, reconstructing invariant features to align with visual representations, thus enhancing the model's group robustness. We further propose a simple sentence augmentation approach, which aims to improve the robustness of CCA-induced subspaces. Our method is simple to implement and can be easily integrated into existing models, making it a practical solution for improving the robustness of vision-language foundation models to group-based biases. The experiments on a variety of datasets demonstrate that our method outperforms existing methods in terms of both performance and robustness.

1 Introduction

Recently, contrastive language-image pretraining (CLIP) and its variants (Radford et al., 2021; Zhai et al., 2023; Desai et al., 2023) are the widely used vision-language models (VLMs). They usually train models on large-scale datasets with a large number of image-text pairs, such as LAION-400M (Schuhmann et al., 2021). Recent works have shown impressive zero-shot generalization on a wide range of tasks, such as medical image classification (Wang et al., 2022), object detection (Ramaswamy et al., 2024), and semantic segmentation (Sun et al., 2024; Li et al., 2024).

However, recent works (Menon & Vondrick, 2022; Roth et al., 2023; An et al., 2024) show that current VLMs lack systematic investigation of the prompts they use. Therefore, they propose modifying the prompts to improve the model's performance, especially its domain generalization ability. Despite their remarkable zero-shot capability, these models are still sensitive to the group-based biases, which are attributes correlated with the ground-truth labels but are not directly related to the classification task (Zhang et al., 2024; Dehdashtian et al., 2024a; Zhu & Zhang, 2025).

A robust classifier should be invariant to spurious correlations, *i.e.*, features that are correlated with the ground-truth labels but are irrelevant to the task, such as group attributes. To this end, numerous debiasing methods have been proposed to enhance group robustness (Zhang & Ré, 2022; Kumar et al., 2022; Kirichenko et al., 2023; Chuang et al., 2023; Dehdashtian et al., 2024c; You et al., 2024; Gao et al., 2024; Phan et al., 2024; Yang et al., 2024). Many of these approaches involve training a lightweight adapter on top of a frozen CLIP model, using data annotated with both target and group labels. However, despite their success, these methods often suffer from critical limitations that we aim to address.

First, the performance of the model is highly dependent on the dataset used for training the newly added adapter architecture, which hinders the generalization ability of the model to other datasets efficiently. Second, other works (Chuang et al., 2023; Yang et al., 2024) employ prompt tuning, but these techniques often rely

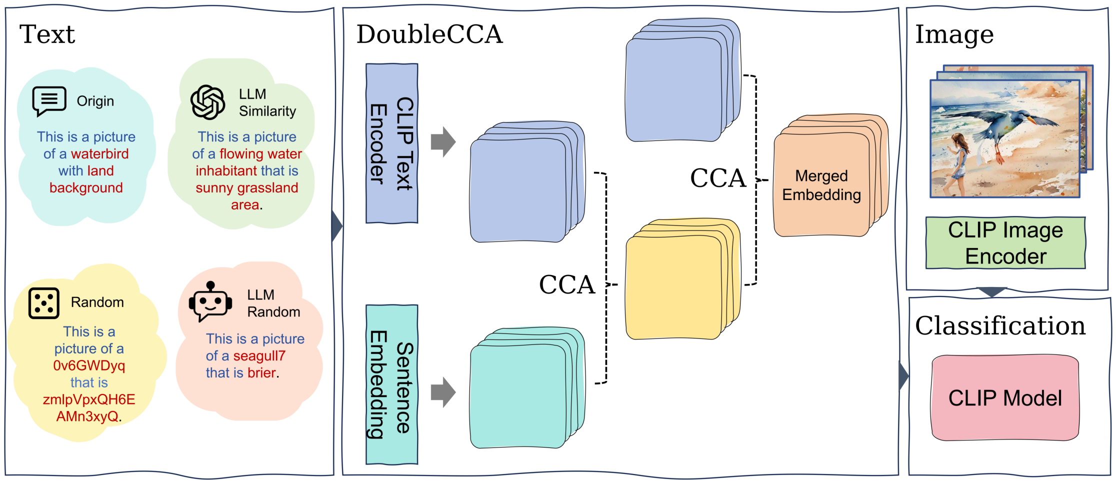


Figure 1: The pipeline of our DoubleCCA. We leverage extra-textual information to augment semantic descriptions and introduce an additional sentence embedding model to complement the semantic limitations of the original VLM text encoder. We use classical CCA technique twice to merge different semantic information, which helps to improve the group robustness of the CLIP model.

on external knowledge. For example, Yang et al. (2024) utilizes an LLM to synthesize a balanced text dataset for tuning. This reliance on prior knowledge of the dataset or large language models makes it challenging to generalize quickly to other datasets and may incur additional API costs. Therefore, current debiasing methods exhibit limitations in generalization and efficiency.

To address these challenges, we ask the following question: *How can we improve the group robustness of the foundation without relying on prior knowledge of the dataset?* To answer this question, we introduce DoubleCCA, a novel framework for enhancing the group robustness of vision-language foundation models (*e.g.*CLIP model) against group-based biases. Our approach is motivated by the observation that CLIP's text encoder has a limited capacity to capture rich semantic information, which can lead to biased representations. Thus, our key idea is to leverage an auxiliary sentence embedding model to generate semantically richer text embeddings, thereby complementing the limitations of the original CLIP text encoder.

Specifically, for a given set of class descriptions, we generate two distinct sets of text embeddings: one from CLIP's text encoder and another from an auxiliary sentence embedding model. We then introduce a two-stage Canonical Correlation Analysis (CCA) framework. The first stage aligns these two embedding sets into a shared, semantically correlated space. The second stage then merges these aligned representations and projects the result back into CLIP's original embedding space to ensure compatibility with the visual features. However, a critical challenge arises when the number of classes is small, as is common in many datasets. This provides insufficient data for CCA to learn stable transformation matrices. To address this, we propose a data augmentation scheme to generate a larger set of diverse sentence embeddings, thereby enabling a more robust estimation of the transformations.

The pipeline of the whole framework is shown in Figure 1, and our contribution can be summarized as follows:

- We propose a novel method, called DoubleCCA, to improve the group robustness of foundation models to group-based biases.
- We introduce an additional sentence embedding model to complement the semantic limitations of the original CLIP text encoder through the CCA technique.
- We show the effectiveness of our method on a variety of datasets, showing that it outperforms existing methods in terms of both group robustness and domain generalization.

In the following sections, we first introduce the necessary background knowledge for our method in Sect. 2, and then present the details of our method in Sect. 3. Finally, we demonstrate the effectiveness of our method on a variety of datasets in Sect. 4.

2 Preliminaries

This section will introduce the necessary background knowledge for our method, including the CLIP foundation model and Canonical Correlation Analysis (CCA).

CLIP model. CLIP model (Radford et al., 2021) is a vision-language foundation model that consists of two parts: a vision encoder and a text encoder. The vision encoder $\Phi_v : \mathbb{R}^{d_v} \to \mathbb{R}^d$ and the text encoder $\Phi_t : \mathbb{R}^{d_t} \to \mathbb{R}^d$ are deep models that map the input image and text to a d-dimensional embedding space, respectively. Given a batch of image-text pairs (I, T), the model is trained to minimize symmetric contrastive loss Radford et al. (2021), which aligns the image-text embedding pairs in the representation space $\mathbb{R}^d$.

Once the model is trained, we can directly use the image and text encoders to align images with text descriptions. Thus, a zero-shot image classifier can be built by comparing the similarity between the image embedding $\Phi_v(I)$ and the text embedding $\Phi_t(T)$. The typical method is to combine the name of the class k with the predefined template to obtain the text description t_k. For example, the class of zebra can be integrated into the prompt template "a photo of a ⟨class name⟩" to yield the description "a photo of a zebra". Thus, we can compute the logits for each class by the cosine similarity between the image embedding and the text embedding, and the class with the highest score is the predicted class.

Group Robustness Metrics. For a model $f : \mathcal{X} \to \mathcal{Y}$, we define the group-specific accuracy as:

$$\mathrm{Acc}_{y,g}(f) = \mathbb{E}_{x\sim\mathcal{D}_{y,g}}[\mathbf{1}(f(x) = y)], \tag{1}$$

where $Acc_{y,g}$ is the accuracy of class y that belongs to group g. The worst-group accuracy, which measures the model's robustness to spurious correlations, is defined as:

$$\mathrm{Acc}_{\text{worst}}(f) = \min_{(y,g)\in\mathcal{Y}\times\mathcal{G}} \mathrm{Acc}_{y,g}(f). \tag{2}$$

A model with high average accuracy but low worst-group accuracy indicates susceptibility to spurious correlations. The robustness gap is defined as:

$$\mathrm{Gap}(f) = \mathbb{E}_{(x,y)\sim\mathcal{D}}[\mathbf{1}(f(x) = y)] - \mathrm{Acc}_{\text{worst}}(f). \tag{3}$$

Canonical Correlation Analysis (CCA). Canonical Correlation Analysis (CCA) is a statistical method that finds the transformation that maximizes the correlation between two feature sets from different models. Let $X_A \in \mathbb{R}^{n\times d_A}$ and $X_B \in \mathbb{R}^{n\times d_B}$ be the data matrices, where n is the number of samples, and d_A and d_B are the dimensions of the feature vectors. CCA finds the transformation matrices W_A and W_B that maximize the correlation between the transformed features $Z_A = X_A W_A$ and $Z_B = X_B W_B$ in a common feature space.

We further define $S^{XX} = X_A^T X_A$ and $S^{YY} = X_B^T X_B$ as the covariance matrices of X_A and X_B, and $S^{XY} = X_A^T X_B$ as the cross-covariance matrix. Therefore, the formulation of CCA can be written as follows:

$$\begin{aligned} \max_{W_A, W_B} \quad & \mathrm{corr}(Z_A, Z_B) = W_A^T S^{XY} W_B \\ \text{s.t.} \quad & W_A^T S^{XX} W_A = I, \quad W_B^T S^{YY} W_B = I, \end{aligned} \tag{4}$$

where $\mathrm{corr}(Z_A, Z_B)$ is the correlation between Z_A and Z_B, and I is the identity matrix.

This formulation can be solved by eigenvalue decomposition of the generalized eigenvalue problem:

$$\begin{aligned} U, S, V^T &= SVD\big((S^{XX})^{-1/2} \cdot S^{XY} \cdot (S^{YY})^{-1/2}\big), \\ W_A &= (S^{XX})^{-1/2} U, \quad W_B = (S^{YY})^{-1/2} V. \end{aligned}$$

In practice, we center the data before applying CCA to ensure the data has a zero mean. And we use regularized CCA (Corrochano et al., 2005; Horoi et al., 2024) to make the computation of W_A and W_B more stable.

Sentence Embedding Models. Sentence embedding models map variable-length sentences to fixed-dimensional dense vectors that capture semantic meaning. Unlike CLIP's text encoder, which is optimized for

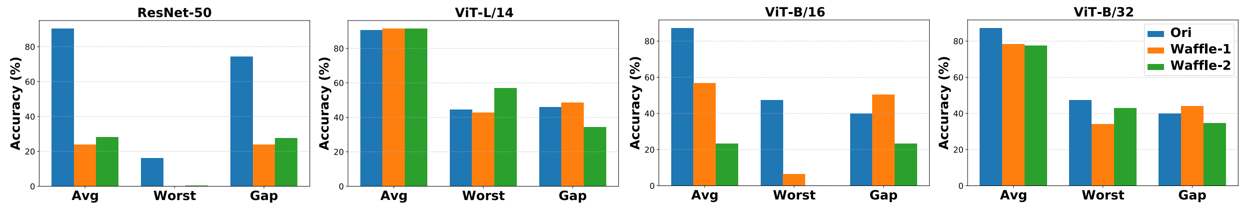


Figure 2: We compare the performance of different prompts with different backbone models on the Waterbirds dataset. "Ori" denotes the original prompt of CLIP, *i.e.*, "a photo of a ⟨class name⟩". "Waffle-1" denotes the combination of the original prompt and the random words, *i.e.*, "a photo of a ⟨class name⟩, which has ⟨random word⟩". "Waffle-2" also denotes the combination of the original prompt and the random words, but with a different template, *i.e.*, "a photo of a ⟨class name⟩, ⟨random characters⟩".

vision-language alignment, dedicated sentence embedding models like Sentence-BERT (Reimers & Gurevych, 2019), HiT (He et al., 2024), BART (Lewis et al., 2020), L12-V2(Reimers & Gurevych, 2020a), and GTE (Li et al., 2023) are trained specifically for semantic similarity tasks. These models learn embedding features where semantically similar sentences are mapped to nearby points in the embedding space, providing complementary information to CLIP's vision-oriented text representations.

3 Method

3.1 Problem Analysis

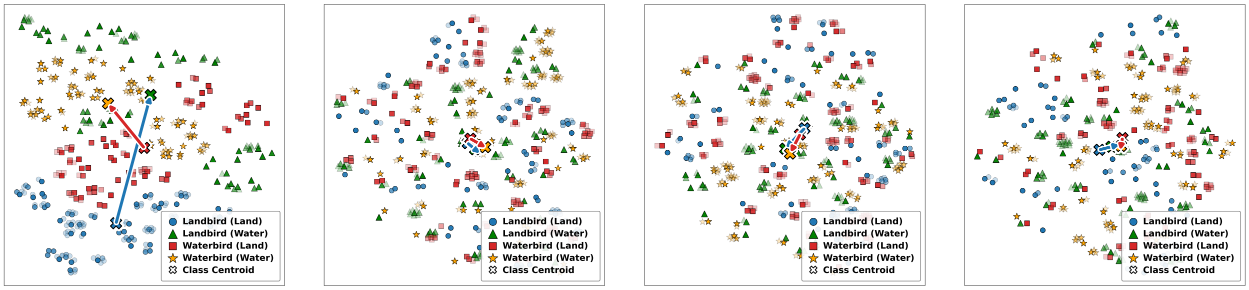
One interesting approach to improve CLIP's zero-shot classification is to augment the prompts with additional visual concepts from external knowledge sources. Menon & Vondrick (2022) utilizes large language models (LLMs) like GPT-3 to generate class-specific descriptions for each class and incorporate them into prompts, resulting in prompts like "a photo of a hen, which has two legs." But this kind of method is limited to prior knowledge of the class name, and the GPT-3-generated descriptions have high degrees of ambiguity and limited visual relevance.

Roth et al. (2023) propose a method called WaffleCLIP, which substitutes GPT-3 generated descriptors with random word or character sequences, resulting in prompts such as "a photo of a hen, which has jmhj, !J#m." Where "jmhj, !J#m" is the random character sequences. Based on WaffleCLIP, we simply study the effect of this method on the group robustness of the CLIP model. We conduct four toy experiments on the Waterbirds dataset (Sagawa et al., 2020) with four different backbone models, *i.e.*, ResNet-50, ViT-B/32, ViT-B/16, and ViT-L/14. We compare the results of vanilla CLIP with the original prompt, WaffleCLIP with random words (shortened as Waffle-1), and WaffleCLIP with random characters (shortened as Waffle-2). See Figure 2.

We observe that WaffleCLIP methods achieve better results in terms of average accuracy and worst-group robustness only when using the ViT-L/14 backbone. However, for the other three backbone models, their performance is worse than vanilla CLIP. Moreover, when using ViT-B/16 or ResNet-50 as the backbone, WaffleCLIP's worst-group robustness drops to near zero, which is substantially lower than that of the original prompt. In other words, WaffleCLIP exhibits inconsistent performance on debiasing tasks, which stands in notable contrast to the empirical findings documented in its original publication.

Although WaffleCLIP enhances semantic representations by incorporating stochastic words, it exhibits persistent deficiencies in semantic enhancement capacity – particularly evident in debiasing tasks. On the other hand, PerceptionCLIP's two-stage paradigm first predicts attribute-specific weighting priors before final category determination. While its empirical results reported in (An et al., 2024) show non-trivial debiasing capabilities, substantial performance gaps persist when benchmarked against state-of-the-art alternatives.

Since WaffleCLIP and PerceptionCLIP do not modify the CLIP text encoder, we believe their suboptimal performance is due to the text encoder failing to produce more semantically meaningful text embeddings. Consequently, we investigate the use of auxiliary text embedding models from natural language processing,



(a) CLIP (b) BART (c) BERT (d) L12-V2

Figure 4: Group-bias visualization of text embeddings across text encoders on the Waterbirds dataset. Each panel shows 2D t-SNE projections of text embeddings from different encoders: (a) CLIP, (b) BART, (c) BERT, (d) L12-V2. Points represent individual text embeddings, with colors indicating class-background combinations. Arrows connect centroids of the same class across different backgrounds (e.g., Landbird on land → Landbird on water). Shorter arrows indicate smaller spurious attribute shifts, demonstrating that auxiliary text encoders (BART, BERT, L12-V2) produce more invariant representations compared to CLIP.

which are designed to generate more informative text representations. We further perform an empirical analysis of CLIP's text representations to support this claim.

Figure 4 illustrates the feature distributions of various sentence embedding models (including the CLIP text encoder, Sentence-BERT, BART, and L12-V2) visualized using t-SNE (van der Maaten & Hinton, 2008) on the Waterbirds dataset that is widely used for evaluating the group robustness. The CLIP text encoder exhibits long arrows between centroids, indicating significant within-class shifts due to spurious background correlations. Conversely, models like BERT and L12-V2 display markedly shorter arrows, demonstrating more invariant representations.

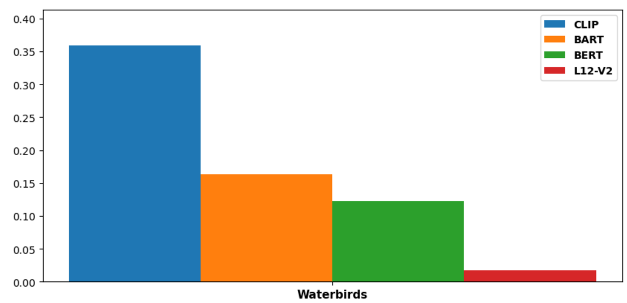


Figure 3: Quantitative comparison of attribute bias across text encoders on Waterbirds datasets. Attribute bias measures the average L2 distance between class-conditional attribute centroids in the embedding space (see Appendix B for details). Lower values indicate more invariant representations.

Moreover, we show the quantitative results on Waterbirds in Figure 3. The CLIP text encoder exhibits a noticeable attribute bias of 0.36, while BERT significantly reduces this bias to 0.12. A similar trend is observed for the other sentence embedding models tested, and preliminary results suggest that this trend also holds for other benchmarks, such as CelebA (see Appendix for details). These results support our claim that auxiliary sentence embedding models are beneficial for extracting more invariant representations. A detailed theoretical motivation for this claim is provided in the Appendix. Therefore, we introduce DoubleCCA, a method that leverages an auxiliary model to effectively enhance the foundation model's performance and group robustness. We will detail our method in the following section.

3.2 DoubleCCA

Based on the previous analysis, our main idea is to utilize these sentence embedding models to enrich the text embeddings of the CLIP model. However, there are two major challenges in this process. First, the dimensionality of the text embeddings generated by the sentence embedding model may not be the same as the text embeddings generated by the CLIP text encoder. Second, it is difficult to merge these newly generated sentence embeddings into the CLIP model. To address these challenges, we propose a novel method, called DoubleCCA, which utilizes the canonical correlation analysis (CCA) technique twice. The first CCA is used to align the representations of different embeddings into a common space. The second CCA is to merge the aligned representations and then recover to the original embedding space.

3.2.1 Step 1: The First CCA

We first generate sentence embeddings using the sentence embedding model Φ_{se} and the CLIP text encoder Φ_t. Let $X \in \mathbb{R}^{n\times d}$ and $X_{se} \in \mathbb{R}^{n\times d_{se}}$ be the data matrices, where n is the number of classes in the dataset, d and d_{se} are the dimensions of the text embeddings generated by the CLIP text encoder and the sentence embedding model, respectively. We then apply CCA (w.r.t. Eq.4) to learn the transformation matrices W_x and W_{se} that embed two features into a common space:

$$Z_x = XW_x, \quad Z_{se} = X_{se}W_{se}, \tag{5}$$

where $Z \in \mathbb{R}^{n\times d_{cca}}$ and $Z_{se} \in \mathbb{R}^{n\times d_{cca}}$ are the aligned representations of the sentence embeddings and the CLIP text embeddings, respectively.

3.2.2 Step 2: The Second CCA.

In zero-shot classification, CLIP computes the similarity between image and text embeddings: $S(I, y) = f_t^T f_v$, where $f_v = \Phi_v(I)$ and $f_t = \Phi_t(T_y)$ for class y. After the First CCA, we achieved two different scores:

$$S_x(I, y) = {x^{(y)}}^T W_x W_x^T f_v,\ S_{se}(I, y) = {x_{se}^{(y)}}^T W_{se} W_x^T f_v, \tag{6}$$

where $x^{(y)}$ and $x_{se}^{(y)}$ are the text embeddings of the class y w.r.t. the original prompts. **Optimal Merging Strategy.** To combine these complementary scores effectively, we formulate the merging as an optimization problem. Let $\hat{W}_x = XW_xW_x^T$ and $\hat{W}_{se} = X_{se}W_{se}W_x^T$ represent the projected text embeddings.

Intuition: The optimal linear combination that maximizes robustness to group shifts while preserving classification accuracy can be achieved through a second CCA that aligns the two predictor spaces.

Following (Horoi et al., 2024), we apply CCA to merge these predictors. First, we construct proxy features:

$$X_A = \hat{W}_x X, \quad X_B = \hat{W}_{se} X, \tag{7}$$

where we use the original text embeddings X as a proxy for image features. We then solve:

$$\max_{P_A, P_B} \quad \mathrm{tr}(P_A^T S_{AB} P_B) \quad \text{s.t. } P_A^T S_{AA} P_A = I, \quad P_B^T S_{BB} P_B = I, \tag{8}$$

where $S_{AA} = X_A^T X_A$, $S_{BB} = X_B^T X_B$, and $S_{AB} = X_A^T X_B$.

The merged text embeddings are:

$$W = \frac{1}{2}(\hat{W}_x + M \cdot \hat{W}_{se}), \quad M = (P_B \cdot P_A^{-1})^T. \tag{9}$$

This merging preserves semantic coherence from both sources while reducing sensitivity to spurious correlations.

Then, we can apply CCA to learn the transformation matrices P_A and P_B via maximization of the correlation between X_A and X_B as follows:

$$\begin{aligned} \max_{P_A, P_B} \quad \mathrm{corr}(X_A, X_B) = P_A^T S^{AB} P_B \quad \text{s.t.} \quad & P_A^T S^{AA} P_A = I, \quad P_B^T S^{BB} P_B = I, \\ & S^{AA} = X_A^T X_A, \quad S^{BB} = X_B^T X_B, \quad S^{AB} = X_A^T X_B. \end{aligned} \tag{10}$$

3.2.3 Data Augmentation for Stable CCA

We note that the number of class labels is usually much smaller. For example, there are only two classes in the Waterbirds dataset. This means that only two sentences are used for the CCA to learn the transformation matrices W_x and W_{se}. We think this is not enough to learn stable transformation matrices. (The next

Algorithm 1 DoubleCCA

Require: Sentence embedding model f_{se}, CLIP model (f_v, f_t), number of augmented sentences K
Ensure: Merged text embeddings W
1: Generate K augmented sentences for each class
2: Extract sentence embeddings F_{rse} using Φ_{se}
3: Extract CLIP text embeddings F_r using Φ_t
4: Apply CCA to X and Y to obtain W_x and W_{se}
5: Compute $\hat{W}_x = XW_xW_x^T$, $\hat{W}_{se} = X_{se}W_{se}W_x^T$
6: Generate augmented sentence embedding features F_r
7: Compute $X_A = \hat{W}_xF_r$, $X_B = \hat{W}_{se}F_r$
8: Apply CCA to X_A and X_B to obtain P_A and P_B
9: Compute $M = (P_B \cdot P_A^{-1})^T$
10: Merge text embeddings: $W = \frac{1}{2}(\hat{W}_x + M \cdot \hat{W}_{se})$
11: **return** W

section will show the experimental verifications.) To address this issue, we propose to use data augmentation to generate more sentence embeddings. First, we combine the original prompt and the random character sequences, *i.e.*, "a photo of a ⟨class name⟩, ⟨random sequences⟩". We call this *random sentence*. Then, we use a large language model (like Qwen) to infer more complementary information that is similar to the original prompt. Third, we concatenate two types of sentences with the original sentences to form a new sentence set, which has a size of K. Finally, we use the sentence embedding model and the CLIP text encoder to extract the corresponding sentence embedding features, *i.e.*, F_{rse} and F_r respectively. We replace X_{se} with F_{rse} and X with F_r to apply CCA to learn the transformation matrices W_x and W_{se}.

3.2.4 Inference

After DoubleCCA, we can achieve the merged text embedding matrix $W \in \mathbb{R}^{n \times d}$. We can directly use these merged text embeddings to predict the class label of the input image, which can be formulated as follows:

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} S(I, y), \text{ where } S(I, y) = W_y \Phi_v(I), \tag{11}$$

where $W_y \in \mathbb{R}^{1 \times d}$ is the y-th row of the merged embedding matrix W, which is the embedding feature of y.

The overall process of DoubleCCA is summarized in Algorithm 1. DoubleCCA is designed as a plug-and-play module, allowing it to be combined with various existing methods such as PerceptionCLIP (PCLIP) (An et al., 2024) and Oth-Cal (Chuang et al., 2023). The specific combination schemes are detailed in the Appendix.

The overall time complexity of our DoubleCCA is: $\mathcal{O}(K(d^2 + d_{se}^2) + d^3)$, where the time complexity of the First CCA is $\mathcal{O}(Kd^2 + Kd_{se}^2 + \min(d, d_{se})^3)$ and the time complexity of the Second CCA is $\mathcal{O}(Kd^2 + d^3)$. In a typical experimental setting (*e.g.*$K \approx 500$, $d = 512$ for ViT-B), DoubleCCA introduces negligible overhead to standard CLIP inference. Since the optimization is convex, it can be solved with eigenvalue decomposition to get a closed-form solution; it's guaranteed to find the best solution and converge reliably.

4 Experiments

4.1 Experimental Setup

Datasets. We evaluate the group robustness of our method. We conduct experiments on two widely used datasets: Waterbirds (Sagawa et al., 2020) and CelebA (Liu et al., 2015). For these two datasets, each image has an associated group attribute, such as the background of the image in the Waterbirds dataset and the gender/age of the person in the CelebA dataset. All these attributes are correlated with the ground truth labels, but they are not directly related to the classification task. Following previous work (Zhang & Ré, 2022), we consider these attributes as group attributes and report the average accuracy and the worst-group robustness on these datasets.

Table 1: Average accuracy and worst-group robustness on the Waterbirds and CelebA dataset. We compare our method with original CLIP and recent PerceptionCLIP, and we select four backbones: ResNet-50, ViT-B/32, ViT-B/16, and ViT-L/14.

		RN50			ViT-B/32			ViT-B/16			ViT-L/14		
		avg.↑	worst↑	gap↓	avg.↑	worst↑	gap↓	avg.↑	worst↑	gap↓	avg.↑	worst↑	gap↓
Waterbirds	CLIP	90.47	16.07	74.40	87.34	47.28	40.06	**87.34**	26.79	60.55	90.55	44.64	45.91
	+background	90.62	39.29	51.33	78.58	61.96	**16.62**	86.01	44.34	44.73	87.72	59.98	27.74
	Ours	**91.76**	44.64	47.30	**89.34**	57.60	31.74	86.53	28.58	57.95	**92.14**	51.78	40.36
	+ background	91.03	**48.21**	**42.82**	85.44	**62.50**	22.94	86.43	**46.43**	**40.00**	89.55	**62.50**	**27.05**
CelebA	CLIP	81.05	73.87	7.18	80.73	75.82	4.91	75.16	62.01	13.15	**86.98**	77.36	9.62
	+gender	85.97	81.58	4.39	80.18	76.18	**4.00**	75.92	66.71	7.99	80.30	74.31	5.99
	+gender,age	87.74	84.94	2.80	82.34	77.21	5.13	75.22	64.61	10.61	82.26	79.06	3.21
	+gender,age,race	85.91	82.57	3.34	81.99	75.67	6.32	76.37	67.93	8.44	82.77	80.00	2.77
	Ours	85.35	83.05	2.30	**84.19**	**78.75**	5.44	79.21	68.54	10.67	85.79	81.18	4.61
	+gender	87.53	85.56	1.97	82.67	76.87	5.80	**78.55**	**73.84**	**4.71**	81.44	76.14	5.30
	+gender,age	**88.70**	**86.35**	2.35	82.16	76.90	5.44	78.09	70.54	7.55	83.78	80.87	2.91
	+gender,age,race	85.93	84.18	**1.75**	82.63	75.92	6.71	77.17	69.18	7.99	85.35	**83.00**	**2.35**

Implementation Details. We utilize CLIP (Radford et al., 2021) as the foundation model and evaluate the performance of our method on a variety of tasks and datasets. All experiments use PyTorch (Paszke et al., 2019) and are performed on a single NVIDIA A100 GPU. We follow the same experimental settings as the previous work (An et al., 2024). We use Resnet-50 (He et al., 2016), ViT-B/32, ViT-B/16, and ViT-L/14 (Dosovitskiy et al., 2021) as the backbone models for the evaluation of group robustness. For the evaluation of domain generalization, we use ViT-B/16 as the backbone model.

For the sentence embedding model, we use the Hierarchy Transformer encoder (HiT) (He et al., 2024) as the default sentence embedding model.[1] Since the output of the HiT lies in the hyperbolic space, we use the logarithmic map function to transform the output to the Euclidean space (Yang et al., 2023). We set the dimension of the common space in the first CCA to 64, and the dimension of the second CCA is set to the dimension of the original image embeddings. Moreover, we set the number of augmented sentences K to 500, which can achieve good results empirically.

4.2 Results on Group Robustness

We first evaluate the group robustness of our method on the Waterbirds and CelebA datasets. The results are reported in Table 1.[2] We mainly evaluate four different backbone models (RN50, ViT-B/32, ViT-B/16, and ViT-L/14). The results are compared between the baseline CLIP model and our proposed method.

First, we show the results when the text prompts only describe the class and ignore the contextual attributes. First, we observe that our method achieves better average accuracy and worst-group robustness than the baseline CLIP model on both datasets. Although the average accuracy of our method is slightly lower than that of the baseline CLIP model, when the backbone is ViT-B/16 on Waterbirds and the backbone is ViT-L/14 on CelebA, the worst-group robustness is significantly improved. We think this is a trade-off between average accuracy and worst-group robustness, which has also been observed in recent work (Dehdashtian et al., 2024b). For example, when the backbone is ViT-L/14 on CelebA, the worst-group robustness of our method is 81.18%, which is higher than that of the baseline CLIP model (77.36%). However, the average accuracy has a slight decrease (from 86.98% to 85.79%) compared to the baseline CLIP model.

Following PerceptionCLIP (An et al., 2024), we include contextual attributes such as conditional information, such as background information in the Waterbirds dataset, and gender information (*i.e.*, female and male) in the CelebA dataset. Here, we only substitute the original prompt embedding with the merged text embeddings W in the CLIP model and then use the same inference process as in (An et al., 2024).

[1] In our experiments, we use "HiT-MiniLM-L12-WordNetNoun" released on HuggingFace as the sentence embedding model.

[2] Note that, in this table, "+background" on the Waterbirds and "+gender, +gender, age, +gender, age, race" on CelebA is the recent PerceptionCLIP method. Ours can be integrated with the PerceptionCLIP method, where we simply replace the original text embeddings with the merged text embeddings, as Eq. 11.

Table 2: Comparison with various state-of-the-art methods on the Waterbirds and CelebA datasets. The backbone model is ViT-L/14.

Method	Waterbird			CelebA		
	avg.	worst	gap	avg.	worst	gap
CLIP	90.55	44.64	45.64	**86.98**	77.36	9.62
WaffleCLIP	91.57	57.14	34.43	84.50	79.35	5.15
Oth-Cal	84.71	67.13	17.58	86.19	76.11	10.08
FairerCLIP	88.87	77.57	11.30	82.57	78.49	4.11
PCLIP	87.72	59.98	27.74	82.77	80.00	2.77
Ours	**92.14**	51.78	40.36	85.79	81.18	4.61
Ours+PCLIP	89.55	62.50	27.05	85.35	83.00	2.35
Ours+Oth-cal	84.04	**80.53**	**3.51**	85.90	**84.51**	**1.39**

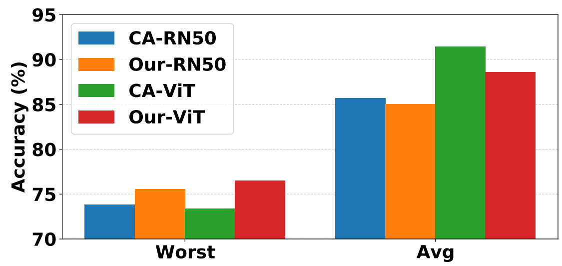


Figure 5: Combination of Contrastive Adapter (CA) and DoubleCCA. We report the average accuracy and worst-group robustness on the Waterbirds dataset. The backbone model is ViT-L/14 and ResNet-50.

We report the results on Waterbirds by considering the background as the contextual attributes, such as in a forest, in the sky, on a street, on grass, on a tree, with flowers, on a beach, with humans, on a branch, etc. First, the same phenomena are observed in our reproduced results, where the group robustness can be improved by incorporating these attributes, which also help reduce the accuracy gap and achieve a more fair zero-shot classifier. Second, we observe that by using our method, the worst-group robustness can be further improved, and the accuracy gap can be further reduced in most cases. More interestingly, considering the background information, the worst-group robustness has a consistent improvement across different backbone models, but the average accuracy has a slight decrease. In this case, a trade-off between average accuracy and worst-group robustness is also observed. But we think this will be of benefit to achieve a more fair zero-shot classifier.

Then, we also report the results on CelebA by considering contextual attributes, such as gender (female and male), age (young and old), race (white skin, dark skin, Asian, and others), etc. We observe that our method can achieve overall better average accuracy and worst-group robustness than the baseline CLIP model on the CelebA dataset. For instance, when the backbone is ViT-B/16, the accuracy gap of our method is 4.71%, which is lower than that of the baseline CLIP model (7.99%), considering the contextual attribute of gender. Furthermore, compared to the results shown in FairerCLIP, our method achieves better results when the backbone is ResNet-50, where the best worst-group robustness of our method is 86.35%, which is higher than that of FairerCLIP (81.50%). For the backbone of ViT-L/14, our method also achieves a competitive result compared to FairerCLIP, where the best worst-group robustness of our method is 83. 00%, which is slightly lower than that of FairerCLIP (85.20%). It is worth noting that FairerCLIP utilizes the target label and attributes to learn a kernel map function in a supervised way, which is more complex than our method.

Third, we compare our method with various state-of-the-art methods, including WaffleCLIP (Roth et al., 2023), PerceptionCLIP (PCLIP) (An et al., 2024), FairerCLIP (An et al., 2024), and Oth-Cal (Chuang et al., 2023). Moreover, since our method can be easily integrated into existing models, we also combine our method with PCLIP and Oth-Cal to further improve the group robustness of the CLIP model. The results are shown in Table 2. We observe that our method can achieve the overall best results on both datasets. Note that, although our method does not achieve the best average accuracy on the CelebA dataset, our method and its combination variants achieve higher worst-group robustness. On the other hand, the results on these two benchmarks show that our method indeed helps reduce the gap between the average accuracy and the worst-group robustness. This means using auxiliary information can help achieve a good trade-off (Dehdashtian et al., 2024b).

Finally, we also combine our method with the contrastive adapter (CA) (Zhang & Ré, 2022) to further improve the group robustness of the CLIP model. In detail, we first use DoubleCCA to generate the merged text embeddings, and then substitute the original text embeddings with the merged text embeddings in the CLIP model. Finally, we use the CA algorithm to learn the adapter. The results are shown in Figure 5. We observe that using the merged text embeddings helps improve the worst-group accuracy, but the average accuracy has a slight decrease. Thus, the trade-off between the average accuracy and the worst-group robustness is also observed.

Overall, the results show that DoubleCCA effectively enhances the group robustness of foundation models, providing better performance and fairness across different datasets and backbone models. In different scenarios, trade-off phenomena are also observed, which is consistent with previous work (Dehdashtian et al., 2024b).

4.3 Effect of Sentence Embeddings

Since DoubleCCA leverages auxiliary sentence embeddings, we conduct an ablation study to analyze the effect of sentence embeddings on the group robustness of the CLIP model.

In previous experiments, we used the HiT model (He et al., 2024) to generate sentence embeddings. To further study the effect of sentence embeddings, we replace the HiT model with other sentence embedding models. To ensure a comprehensive comparison, we select popular models from HuggingFace Hub[3] as alternatives to the default HiT model, such as the classical Sentence-BERT model (BERT) (Reimers & Gurevych, 2020b), gte-base-en-v1.5 model (GTE) (Li et al., 2023), and bart-base model (BART) (Lewis et al., 2020). We directly use the pre-trained models released by HuggingFace Hub to generate sentence embeddings for the Waterbirds dataset. The results are shown in Figure 6.

Compared with the original CLIP model, we observe that different sentence embedding methods in DoubleCCA either improve the model's performance or maintain it at a comparable level. Notably, HiT demonstrates the most significant improvements in performance. Both Sentence-BERT and gte-base-en-v1.5 also have a positive impact on the model's performance.

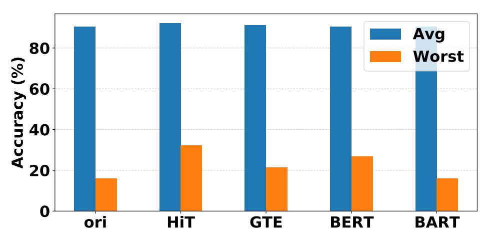
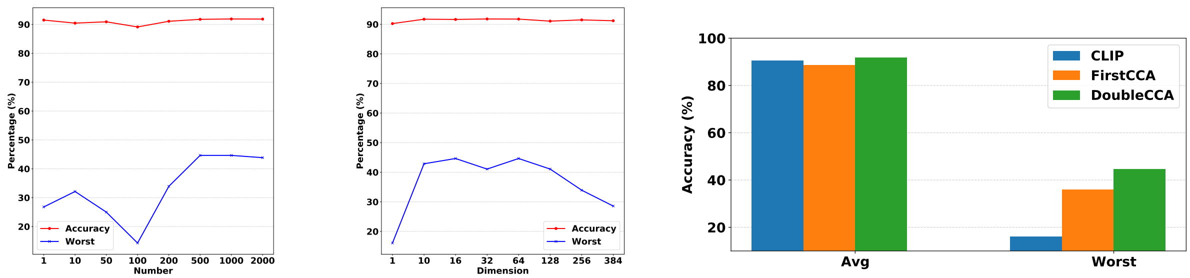


Figure 6: The impact of different sentence embedding models. We conduct experiments on the Waterbirds and report the average accuracy (Avg) and worst-group robustness (WG).

First, HiT is a state-of-the-art sentence embedding model that aims to learn the hierarchical semantic structure in language models. HiT is trained on WordNet, which can provide unseen subsumptions and hypernyms for the words in the sentence. Second, Sentence-BERT and gte-base models are also popular sentence embedding models, which are verified to be effective in unsupervised text retrieval tasks. However, BART shows little improvement in model performance. We think this is because BART targets dialogue understanding, question answering, and summarization tasks, which may face the same problems as mentioned before, where it will introduce semantic ambiguity to text embeddings (Menon & Vondrick, 2022).

Overall, the results demonstrate that the choice of the sentence embedding model can significantly affect the performance of the foundation model. We recommend using HiT as the default sentence embedding model in DoubleCCA, as it achieves the best performance in our experiments. Moreover, it is more interesting to

[3]`https://huggingface.co/`



(a) # of augmented sentences (b) Dimension of CCA (c) Effect of the first CCA

Figure 7: Ablation study results on the Waterbirds dataset.

explore the effect of different sentence embedding models on the group robustness of the foundation model, which is left for future work.

4.4 Ablation Study

4.4.1 Effect of the Hyperparameters.

Number of Sentences. We conduct an ablation study to analyze the effect of the number of augmented sentences on the group robustness. We employ the backbone model for ResNet-50 and fix the dimension of the CCA as 64. Then, we vary the number of sentences from 1 to 2000. The results are shown in Figure 7 (a). The results indicate that varying the number of sentences has minimal impact on the average accuracy but demonstrates a substantial influence on the worst-group robustness. When the number of sentences is less than 500, the worst-group robustness exhibits high variability. In particular, when the number of sentences drops to 100, the performance deteriorates below that of the original CLIP model. We attribute this instability to the inherent randomness of the part of random sentences. However, as the number of sentences increases, the model's performance gradually stabilizes, suggesting that sufficient sentences enable the model to capture meaningful pragmatic information.

Dimension of CCA. We further study the effect of the dimension of the CCA on the group robustness of the CLIP model. We employ the ResNet-50 backbone model and fix the number of sentences to 500. Then, we vary the dimension of the CCA from 1 to 384[4]. The results are shown in Figure 7 (b). The results indicate that the dimension of the common space significantly impacts performance. Both low and high dimensions adversely affect the results; low dimensions lead to insufficient feature representation, while high dimensions introduce feature vectors corresponding to small singular values. We recommend setting the dimension of the CCA to 64, as it achieves the best performance in our experiments. Moreover, as discussed in (Vidal et al., 2016), the dimension of this subspace is a natural measure of the model complexity; thus, some automatic dimension selection methods can be used to determine the optimal dimension of the CCA. We leave this for future work.

4.4.2 Effect of the First CCA

Finally, we analyze the effect of the first CCA on the group robustness of the CLIP model. We employ the backbone model to ResNet-50 and fix the number of sentences to 500. Then, we remove the second CCA from the DoubleCCA method and directly use Eq.6 as the score function for the zero-shot classification. The results are shown in Figure 7 (c). The results indicate that only the first CCA has a positive impact on the group robustness of the CLIP model. But the second CCA step is essential for further improving the group robustness of the CLIP model.

4.4.3 Effect of the Data Augmentation

We further study the effect of data augmentation on the group robustness of the CLIP-ViT-L/14 on CelebA. Then, we consider four different scenarios: (a) only using the original prompt (S1); (b) using the original

[4]The dimension of the HiT feature is 384.

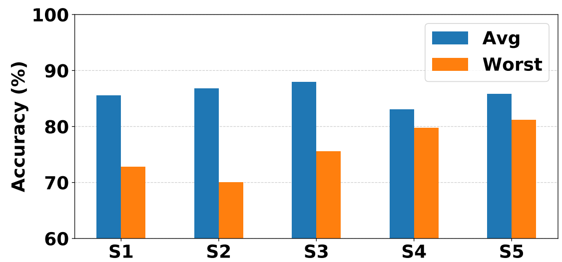


Figure 8: Accuracy of ViT-L/14 on CelebA with five different data augmentation methods (more details can be seen in Sec. 4.4.3). We report the average accuracy (Avg) and worst-group robustness (WG).

prompt and random character sequences (S2); (c) using the original prompt and its variants that contain the attribute information (S3); (d) using the original prompt and LLM-generated sentences (S4); (e) using the original prompt, random sentences, and LLM-generated sentences (S5); The results are shown in Figure 8. We can observe that different data augmentation methods affect the performance. If we only use the original prompts, the results are worse. This verifies our assumption that the original prompt is not enough to learn stable transformation matrices. Moreover, although random sentences help performance improvements, their average is the lowest one. Thus, when we combine them with LLM-generated sentences, the performance can be further improved and can achieve a good trade-off between average accuracy and group robustness.

5 Related Work

This section will briefly review related work in group robustness. Group robustness is a critical issue in machine learning, especially in the context of fairness and bias. There are many works that focus on improving the group robustness of foundation models. Existing methods can be divided into two categories: prompt tuning, adapter-based methods, and fine-tuning methods. The first category includes methods that modify the input prompts given to a pre-trained model to better align with the desired output. Representative works include (Chuang et al., 2023; Phan et al., 2024; Yang et al., 2024). The second category includes methods that add additional modules to the pre-trained model to adapt it to the target task. Representative works include (Zhang & Ré, 2022; Gao et al., 2024; Dehdashtian et al., 2024c). The third category includes methods that fine-tune the pre-trained model on the target task. The representative works include (Kumar et al., 2022). In addition to these methods, An et al.(An et al., 2024) proposes a perception-aware method (called PerceptionCLIP) to enhance the group robustness of the CLIP model, which provides CLIP with contextual attributes. This is similar to our method, which also enriches the text embeddings of the CLIP model with additional semantic information. Both of us aim to improve the group robustness of the zero-shot classifier. According to the experiments, our method outperforms PerceptionCLIP in terms of both average accuracy and worst-group robustness. Since our method is simple and easy to implement, it can be easily integrated into existing models, such as the contrastive adapter (Zhang & Ré, 2022), providing a practical solution to improve the robustness of the foundation models.

6 Conclusion

We proposed DoubleCCA, a novel method to improve the robustness of foundation models to group-based biases. By employing CCA twice, our method effectively aligns and merges different text representations. We demonstrated the effectiveness of DoubleCCA on various datasets, showing that it outperforms existing methods in terms of both group robustness and domain generalization. Our approach is simple to implement and can be easily integrated into existing models, providing a practical solution to improve the robustness of foundation models. Future work could explore the theoretical foundations of this approach and further design a black-box optimization scheme (Song et al., 2024) to enhance robustness.

References

Bang An, Sicheng Zhu, Michael-Andrei Panaitescu-Liess, Chaithanya Kumar Mummadi, and Furong Huang. PerceptionCLIP: Visual classification by inferring and conditioning on contexts. In *ICLR*, 2024.

Ching-Yao Chuang, Varun Jampani, Yuanzhen Li, Antonio Torralba, and Stefanie Jegelka. Debiasing vision-language models via biased prompts. *arXiv:2302.00070*, 2023.

Eduardo Bayro Corrochano, Tijl De Bie, Nello Cristianini, and Roman Rosipal. Eigenproblems in pattern recognition. *Handbook of Geometric Computing: Applications in Pattern Recognition, Computer Vision, Neuralcomputing, and Robotics*, 2005.

Sepehr Dehdashtian, Ruozhen He, Yi Li, Guha Balakrishnan, Nuno Vasconcelos, Vicente Ordonez, and Vishnu Naresh Boddeti. Fairness and bias mitigation in computer vision: A survey. *arXiv preprint arXiv:2408.02464*, 2024a.

Sepehr Dehdashtian, Bashir Sadeghi, and Vishnu Naresh Boddeti. Utility-fairness trade-offs and how to find them. In *CVPR*, 2024b.

Sepehr Dehdashtian, Lan Wang, and Vishnu Boddeti. FairerCLIP: Debiasing CLIP's zero-shot predictions using functions in RKHSs. In *ICLR*, 2024c.

Karan Desai, Maximilian Nickel, Tanmay Rajpurohit, Justin Johnson, and Shanmukha Ramakrishna Vedantam. Hyperbolic image-text representations. In *ICML*, 2023.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *ICLR*, 2021.

Peng Gao, Shijie Geng, Renrui Zhang, Teli Ma, Rongyao Fang, Yongfeng Zhang, Hongsheng Li, and Yu Qiao. Clip-adapter: Better vision-language models with feature adapters. *IJCV*, 2024.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.

Yuan He, Zhangdie Yuan, Jiaoyan Chen, and Ian Horrocks. Language models as hierarchy encoders. In *NeurIPS*, 2024.

Stefan Horoi, Albert Manuel Orozco Camacho, Eugene Belilovsky, and Guy Wolf. Harmony in diversity: Merging neural networks with canonical correlation analysis. In *ICML*, 2024.

Polina Kirichenko, Pavel Izmailov, and Andrew Gordon Wilson. Last layer re-training is sufficient for robustness to spurious correlations. In *ICLR*, 2023.

Ananya Kumar, Aditi Raghunathan, Robbie Matthew Jones, Tengyu Ma, and Percy Liang. Fine-tuning can distort pretrained features and underperform out-of-distribution. In *ICLR*, 2022.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *ACL*, 2020.

Yunheng Li, Zhong-Yu Li, Quan-Sheng Zeng, Qibin Hou, and Ming-Ming Cheng. Cascade-clip: Cascaded vision-language embeddings alignment for zero-shot semantic segmentation. In *ICML*, 2024.

Zehan Li, Xin Zhang, Yanzhao Zhang, Dingkun Long, Pengjun Xie, and Meishan Zhang. Towards general text embeddings with multi-stage contrastive learning. *arXiv:2308.03281*, 2023.

Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In *ICCV*, 2015.

Sachit Menon and Carl Vondrick. Visual classification via description from large language models. In *ICLR*, 2022.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *NeurIPS*, 2019.

Hoang Phan, Andrew Gordon Wilson, and Qi Lei. Controllable prompt tuning for balancing group distributional robustness. In *ICML*, 2024.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *ICML*, 2021.

Vikram V Ramaswamy, Sing Yu Lin, Dora Zhao, Aaron Adcock, Laurens van der Maaten, Deepti Ghadiyaram, and Olga Russakovsky. Geode: a geographically diverse evaluation dataset for object recognition. *NeurIPS*, 2024.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*, 2019.

Nils Reimers and Iryna Gurevych. Making monolingual sentence embeddings multilingual using knowledge distillation. *arXiv preprint arXiv:2004.09813*, 2020a.

Nils Reimers and Iryna Gurevych. Making monolingual sentence embeddings multilingual using knowledge distillation. In *EMNLP*, 2020b.

Karsten Roth, Jae Myung Kim, A Koepke, Oriol Vinyals, Cordelia Schmid, and Zeynep Akata. Waffling around for performance: Visual classification with random words and broad concepts. In *ICCV*, 2023.

Shiori Sagawa, Pang Wei Koh, Tatsunori B. Hashimoto, and Percy Liang. Distributionally robust neural networks. In *ICLR*, 2020.

Christoph Schuhmann, Richard Vencu, Romain Beaumont, Robert Kaczmarczyk, Clayton Mullis, Aarush Katta, Theo Coombes, Jenia Jitsev, and Aran Komatsuzaki. Laion-400m: Open dataset of clip-filtered 400 million image-text pairs. *arXiv:2111.02114*, 2021.

Xingyou Song, Yingtao Tian, Robert Tjarko Lange, Chansoo Lee, Yujin Tang, and Yutian Chen. Position: Leverage foundational models for black-box optimization. In *ICML*, 2024.

Shuyang Sun, Runjia Li, Philip Torr, Xiuye Gu, and Siyang Li. Clip as rnn: Segment countless visual concepts without training endeavor. In *CVPR*, 2024.

Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *JMLR*, 2008.

René Vidal, Yi Ma, S Shankar Sastry, René Vidal, Yi Ma, and S Shankar Sastry. Principal component analysis. *Generalized principal component analysis*, 2016.

Zifeng Wang, Zhenbang Wu, Dinesh Agarwal, and Jimeng Sun. Medclip: Contrastive learning from unpaired medical images and text. *arXiv:2210.10163*, 2022.

Menglin Yang, Min Zhou, Rex Ying, Yankai Chen, and Irwin King. Hyperbolic representation learning: Revisiting and advancing. In *ICML*, 2023.

Yunfan Yang, Chaoquan Jiang, Zhiyu Lin, Jinlin Xiao, Jiaming Zhang, and Jitao Sang. Debiasing vison-language models with text-only training. *arXiv:2410.09365*, 2024.

Chenyu You, Yifei Mint, Weicheng Dai, Jasjeet S Sekhon, Lawrence Staib, and James S Duncan. Calibrating multi-modal representations: A pursuit of group robustness without annotations. In *CVPR*, 2024.

Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In *ICCV*, 2023.

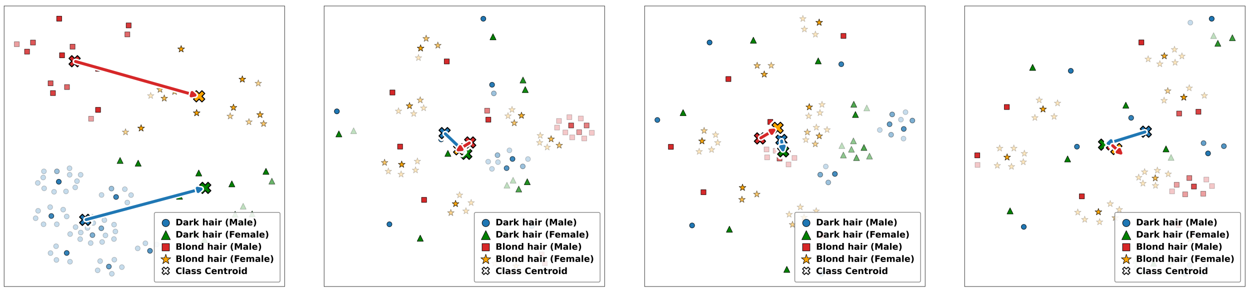
Jingyi Zhang, Jiaxing Huang, Sheng Jin, and Shijian Lu. Vision-language models for vision tasks: A survey. *IEEE transactions on pattern analysis and machine intelligence*, 46(8):5625–5644, 2024.

Michael Zhang and Christopher Ré. Contrastive adapters for foundation model group robustness. *NeurIPS*, 2022.

Beier Zhu and Hanwang Zhang. Debiasing vision-language models for vision tasks: a survey. *Frontiers of Computer Science*, 19(1), 2025.

A Visualization results on CelebA

Figure 9 shows similar patterns on the CelebA dataset, where arrows connect same-class centroids across gender attributes (Male → Female). CLIP's representations exhibit large gender-induced shifts, as indicated by long arrows. In contrast, auxiliary encoders keep within-class clusters compact and are less sensitive to spurious gender attributes. Complementing these visualizations, Figure 10 provides a quantitative summary of the centroid shifts by reporting the mean ℓ_2 distance between male and female centroids within each class (lower is better) and confirms that auxiliary encoders consistently yield smaller cross-gender distances than CLIP, consistent with the t-SNE trends.



(a) CLIP (b) BART (c) BERT (d) L12-V2

Figure 9: Group-bias visualization of text embeddings across text encoders on the CelebA dataset. Each panel shows 2D t-SNE projections from: (a) CLIP, (b) BART, (c) BERT, (d) L12-V2. Points represent text embeddings colored by class-gender combinations. Arrows connect same-class centroids across gender attributes (Male → Female). The substantially shorter arrows in BART, BERT, and L12-V2 compared to CLIP indicate these auxiliary encoders learn representations that are more robust to spurious gender correlations.

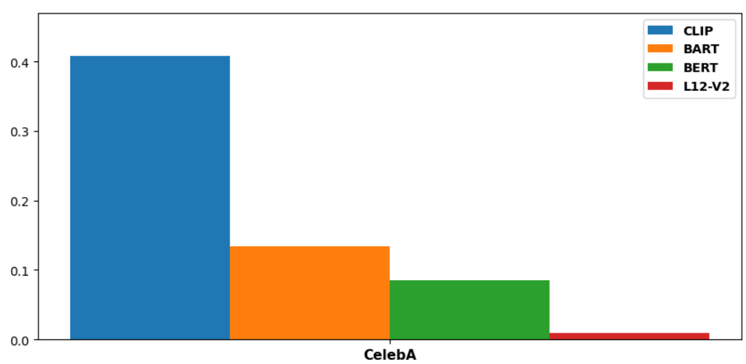


Figure 10: Quantitative comparison of attribute bias across text encoders on CelebA datasets. Attribute bias measures the average L2 distance between class-conditional attribute centroids in the embedding space (see Appendix B for details). Lower values indicate more invariant representations.

B Attribute Bias Score Computation

The Attribute Bias Score (ABS) used in Figure 3 and Figure 10 quantifies how much text representations shift due to spurious attributes within each class. Given a text encoder Φ, we compute:

- **Class-attribute centroids**: For each class $c \in \mathcal{C}$ and attribute $a \in \mathcal{A}$, we compute the centroid of all text embeddings:
$$\boldsymbol{\mu}_{c,a} = \frac{1}{N_{c,a}} \sum_{i:y_i=c,a_i=a} \Phi(\mathbf{t}_i) \tag{12}$$
where $N_{c,a}$ is the number of text samples with class c and attribute a, and $\mathbf{t}_i$ represents the i-th text prompt.

- **Within-class attribute shift**: For each class c, we measure the L_2 distance between centroids across different attributes:
$$d_c = \|\boldsymbol{\mu}_{c,0} - \boldsymbol{\mu}_{c,1}\|_2 \tag{13}$$

- **Overall Attribute Bias Score**:
$$\text{ABS}(\Phi) = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} d_c \tag{14}$$
where $|\mathcal{C}|$ is the number of classes.

For the **Waterbirds** dataset, this metric captures how text representations of "landbird" and "waterbird" shift between land and water backgrounds. For **CelebA**, it measures shifts between male and female attributes for hair color classes. A lower ABS indicates that the encoder produces more invariant representations that are robust to spurious correlations.

C Integration with Existing Methods.

DoubleCCA can be easily integrated with other robustness methods:

- **With PerceptionCLIP:** Replace their text embeddings with our merged embeddings W
- **With Contrastive Adapters:** Use W as input to the adapter module
- **With prompt engineering methods:** Apply DoubleCCA to any engineered prompts

The modular nature of our approach allows it to enhance existing methods without architectural changes.

D Theoretical Motivation.

Semantic Structure. Let $\mathcal{T}$ be the space of text descriptions. The semantic structure is characterized by a similarity function
$$s : \mathcal{T} \times \mathcal{T} \longrightarrow [0, 1]$$
that captures linguistic relationships between texts.

Structure Preservation. An encoder $\Phi : \mathcal{T} \to \mathcal{E}$ preserves semantic structure if, for some small $\epsilon > 0$, it holds that
$$\forall\, t_1, t_2 \in \mathcal{T} : \quad \big|s(t_1, t_2) \ - \ \cos\big(\Phi(t_1), \Phi(t_2)\big)\big| < \epsilon.$$

Proposition 1. The CLIP text encoder $\Phi_t : \mathcal{T} \to \mathcal{E}_{\text{CLIP}}$, being optimized for vision–language alignment, induces a bias towards visual discriminability that can distort purely linguistic semantic structure—particularly when classes exhibit spurious visual correlations.

Proof. Consider the CLIP training objective
$$\mathcal{L}_{\text{CLIP}} = -\mathbb{E}_{(I,T)\sim\mathcal{D}}\left[\log \frac{\exp\big\langle \Phi_v(I), \Phi_t(T)\big\rangle/\tau}{\sum_{T' \in \mathcal{B}} \exp\big\langle \Phi_v(I), \Phi_t(T')\big\rangle/\tau}\right].$$

Taking the gradient with respect to the text embedding yields a term that pushes $\Phi_t(T)$ toward its paired visual feature $\Phi_v(I)$ and away from others. If two semantically similar texts t_1, t_2 (e.g. "waterbird" vs. "seabird") happen to co-occur with very different visual contexts I_1, I_2, then to satisfy

$$\langle \Phi_t(t_1), \Phi_v(I_1) \rangle \gg \langle \Phi_t(t_1), \Phi_v(I_2) \rangle \quad \text{and} \quad \langle \Phi_t(t_2), \Phi_v(I_2) \rangle \gg \langle \Phi_t(t_2), \Phi_v(I_1) \rangle,$$

one must force $\|\Phi_t(t_1) - \Phi_t(t_2)\|$ large, contradicting their high linguistic similarity. Hence, the encoder trades off semantic preservation for visual discriminability when spurious cues are strong.

Corollary 1. For datasets with strong spurious correlations (strength ρ) between visual features and class labels, the expected distortion in the text-embedding space grows proportionally to ρ.

Proof Sketch. One can show

$$\mathbb{E}\big[\|\Phi_t(t_1) - \Phi_t(t_2)\|\big] \ \gtrsim \ c\,\rho\,\big\|\mathbb{E}[\Phi_v(I_1)] - \mathbb{E}[\Phi_v(I_2)]\big\|,$$

for some constant $c > 0$ depending on τ and $|\mathcal{D}|$.

Lemma (Information Decomposition). For any text $T \in \mathcal{T}$, its total information $H(T)$ decomposes as

$$H(T) = I(T; \mathcal{V}) \ + \ I\big(T; \mathcal{L} \mid \mathcal{V}\big) \ + \ H\big(T \mid \mathcal{V}, \mathcal{L}\big),$$

where $\mathcal{V}$ denotes visual concepts and $\mathcal{L}$ denotes pure linguistic structure.

Proposition (Complementary Encoders). Let Φ_t be CLIP's text encoder and Φ_{se} a sentence-only encoder. Then

$$I\big(\Phi_t(T); \mathcal{V}\big) \ > \ I\big(\Phi_{se}(T); \mathcal{V}\big), \quad I\big(\Phi_{se}(T); \mathcal{L} \mid \mathcal{V}\big) \ > \ I\big(\Phi_t(T); \mathcal{L} \mid \mathcal{V}\big).$$

Proof Sketch. CLIP's objective maximizes alignment with visual features (hence upper-bounds $I(\Phi_t(T); \mathcal{V})$), whereas sentence encoders optimize for textual mutual information across related sentences (preserving linguistic structure).

E Additional Ablation Studies on Data Augmentation

To further investigate the contribution of each component in our data augmentation strategy, we conducted detailed ablation experiments on the CelebA dataset using ViT-L/14. We systematically evaluated four different configurations:

- **S-(1)**: Baseline using only the original CLIP prompt template "a photo of a {class}"
- **S-(2)**: Original prompt augmented with random character sequences
- **S-(3)**: Original prompt augmented with LLM-generated contextual descriptions
- **S-(4)**: Full augmentation combining original prompt, random sequences, and LLM-generated descriptions

Table 3: Ablation study of data augmentation strategies on CelebA (ViT-L/14). S-(1): original prompt only; S-(2): original + random sequences; S-(3): original + LLM descriptions; S-(4): all combined.

	S - (1)	S - (2)	S - (3)	S - (4)
Worst	51.44	38.93	67.73	88.24
Avg	52.84	39.47	68.82	88.35

The results in Table 3 reveal several key insights:

Random sequences alone are detrimental (S-2): Using only random character augmentation significantly degrades performance (38.93% worst-group accuracy vs. 51.44% baseline), confirming that meaningful semantic augmentation is crucial.

LLM-generated descriptions provide improvement (S-3): Augmenting with semantically meaningful LLM-generated sentences improves worst-group accuracy to 67.73%, demonstrating the value of coherent linguistic variations.

Combining all augmentation strategies is optimal (S-4): The full augmentation strategy achieves the best performance (88.24% worst-group accuracy), suggesting that the diversity from both random perturbations and semantic variations helps CCA learn more robust transformation matrices.

These findings validate our design choice of using combined augmentation (S-4) in the main experiments, as it provides sufficient data diversity for stable CCA estimation while maintaining semantic coherence.