DrML: Diagnosing and Rectifying Vision Models using Language

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Abstract

Recent multi-modal contrastive learning models have demonstrated the ability to learn an embedding space suitable for building strong vision classifiers, by leveraging the rich information in large-scale image-caption datasets. Our work highlights a distinct advantage of this multi-modal embedding space: the ability to diagnose vision classifiers through natural language. The traditional process of diagnosing model behaviors in deployment settings involves labor-intensive data acquisition and annotation. Our proposed method, *DrML*, can discover high-error data slices, identify influential attributes and further rectify undesirable model behaviors, without requiring any visual data. Through a combination of theoretical explanation and empirical verification, we present conditions under which classifiers trained on embeddings from one modality can be equivalently applied to embeddings from another modality. On a range of image datasets with known error slices, we demonstrate that our method can effectively identify the error slices and influential attributes, and can further use language to rectify failure modes of the classifier.

1 Introduction

Recent models trained using multi-modal contrastive learning have leveraged large-scale datasets of aligned image-caption pairs to obtain shared embedding spaces that capture rich visual and textual features. The learned image and text encoders resulting from multi-modal contrastive learning have been demonstrated to be effective feature extractors that can be used to train strong single-modality classifiers (Radford et al., 2021). In this work, we show how visual classification models obtained through multi-modal contrastive learning, as described above, offer a significant additional advantage: the ability to use language to probe and diagnose the behavior of the vision models.

Model diagnosis aims to gain a systematic and comprehensive understanding of when and why models fail. This is a critical quality assurance process to prevent unexpected and catastrophic failures of models in high-stake settings. A growing body of work has proposed methods for addressing this need. For example, error slice discovery methods aim to find subsets of inputs with similar characteristics where the model performs significantly worse (d'Eon et al., 2022; Eyuboglu et al., 2022). Interpretability methods aim to understand the black-box process of model prediction and thus the reasons why models fail for certain inputs (Ribeiro et al., 2016; Koh et al., 2020).

While these prior efforts have made progress in vision model diagnosis, they all suffer from a critical Achilles' heel — *susceptibility to lack of visual data*. Curated training and test sets from the same data distribution are typically used to develop vision models. Even if models achieve perfect performance on these datasets, their performance can degrade drastically when deployed in-the-wild, due to distribution shifts (Koh et al., 2021; Wiles et al., 2022). Yet most existing model diagnosis methods require visual examples of failure modes (e.g., present in the test set) to discover them. As a result,

Submitted to the Workshop on Distribution Shifts, 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

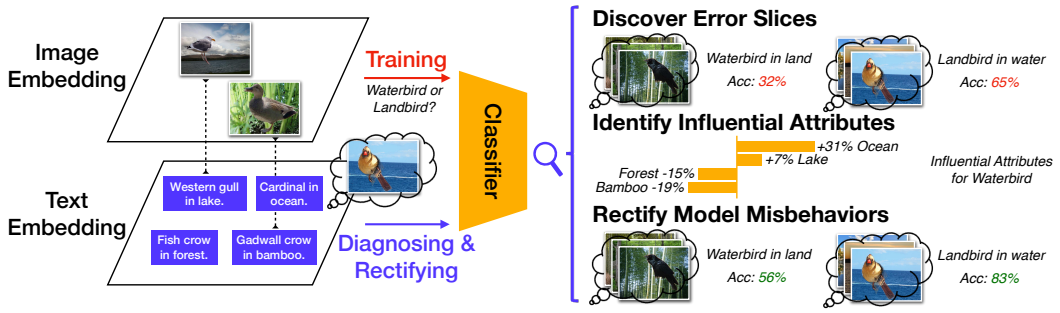

Figure 1: **Overview of our approach, DrML, that diagnoses and rectifies vision models using language.** Our approach leverages the shared image and text representation space learned by multi-modal contrastive learning. We find that classifiers trained on embeddings from one modality can be equivalently applied to embeddings from another modality, despite the fact that embeddings from these two modalities are distinctly separated. This cross-modal transferability phenomenon enables us to diagnose a vision model by training it on the image embedding space and probing it with text embeddings. The use of language allows us to generate a large set of diverse and novel inputs to discover error slices, identify influential attributes, and rectify model misbehaviors.

using these methods is reliant on efforts to collect large-enough datasets to cover all data distributions and potential failure modes of interest, which is often impractical or infeasible.

The goal of our work is to circumvent this need to collect test data representing all data distributions of interest, and instead use natural language input to diagnose vision classifiers. It is often easier to generate a set of diverse natural language inputs by combining known attributes and prompt generators than to collect a set of image inputs representing the same desired concepts. We observe that vision classifiers trained on image embeddings from a shared image-text embedding space suggest the possibility of leveraging text embeddings as a proxy for image embeddings. Multi-modal contrastive losses are frequently used to learn such shared embedding spaces. However, while these losses encourage image and text embeddings to be closer for aligned pairs than for mismatched pairs, there is no guarantee that in practice, using text embeddings as input into a vision classifier trained on the image embeddings will result in the same predictions. In this work, we first verify that text inputs can indeed work as good proxies to image inputs trained on a shared image-text embedding space obtained through contrastive learning. We refer to this as *cross-modal transferability*.

Based on the phenomenon of cross-modal transferability, we then present **DrML** for **D**iagnosing and **R**ectifying Vision **M**odels using **L**anguage. We show that DrML can use language to *diagnose* vision models in two different ways: discovering error slices including concepts for which we have no visual data, and identifying attributes that have the greatest impact on model predictions. Finally, we present a method that uses language to *rectify* undesirable behaviors without requiring the collection of more visual data. Figure 1 illustrates our framework for diagnosing and rectifying vision models using language. On three image datasets representing the three most common types of model failure modes, we demonstrate that DrML can effectively identify error slices and influential attributes, and can further rectify these model failure modes using language (Appendix A).

2 Approach

We first define basic notations used in this paper. Given a pre-trained multi-modal contrastive model, along with an image $X \in \mathcal{X}$ or text $Y \in \mathcal{Y}$ as input, we can obtain their l_2-normalized embeddings $\boldsymbol{x}$ or $\boldsymbol{y}$ from the image encoder $f_x : \mathcal{X} \mapsto \mathbb{R}^d$ or the text encoder $f_y : \mathcal{Y} \mapsto \mathbb{R}^d$, respectively, where d is the dimension of the shared multi-modal embedding space. We can build classifiers $h : \mathbb{R}^d \mapsto \mathcal{C}$ such as a linear layer or multi-layer perception on the shared embedding space to predict the label $c \in \mathcal{C}$ given an image embedding or text embedding. We focus on the case of vision classifiers trained using image embeddings.

2.1 Text Embeddings as Proxies for Image Embeddings

The core of our work hinges on the ability to use text as a proxy for image inputs, thereby enabling us to use language to diagnose vision models. Here we describe our approach to analyze if this is feasible in practice — *are text inputs good proxies for images in contrastive representation space?*

Cross-modal Transferability. To answer the question, we first define cross-modal transferability. Let $P_{\mathcal{D}}$ be the joint data distribution over image-text pairs. For $X, Y \sim P_{\mathcal{D}}$, we denote $\boldsymbol{x} = f_x(X)$ and $\boldsymbol{y} = f_y(Y)$ the corresponding image and text embeddings respectively. We say that a vision classifier h achieves cross-modal transferability when it outputs similar predictions on $\boldsymbol{x}$ and $\boldsymbol{y}$. In other words, the difference across the prediction pair is small:

$$\mathbb{E}_{\boldsymbol{x},\boldsymbol{y}}[D(h(\boldsymbol{x}), h(\boldsymbol{y}))] \approx 0,$$

where $D(\cdot,\cdot)$ measures the difference between predictions, e.g. the 0-1 loss $D(u, v) = \mathbf{1}_{u \neq v}$.

Modality Gap. While intuition suggests that embeddings of a matched image-caption pair should be close, recent work shows instead that the embeddings are approximately clustered per modality (Liang et al., 2022). They refer to the distance between these clusters as the *modality gap*. We define the individual-level modality gap $\boldsymbol{g}$ as the difference between image and text embeddings for a single pair, and the class-level gap $\boldsymbol{g}_c$ as the average difference between image and text embeddings for a given class $c \in \mathcal{C}$. Formally, the modality gap definitions are written as:

$$\boldsymbol{g} = \boldsymbol{x} - \boldsymbol{y} \text{ and } \boldsymbol{g}_c = \boldsymbol{x}_c - \boldsymbol{y}_c, \text{ where}$$
$$\boldsymbol{x}_c = \mathbb{E}_{X \sim P_{\mathcal{D}}(X|c)}[f_x(X)], \quad \boldsymbol{y}_c = \mathbb{E}_{Y \sim P_{\mathcal{D}}(Y|c)}[f_y(Y)].$$

Modality Gap Geometry. We take a closer look at the modality gap geometry across a range of multi-modal contrastive models and datasets, presented in detail in Section A.2, and empirically find that the following hold true:

1. *The modality gap between corresponding image and text embeddings can be approximated by a constant vector, particularly at the class level.*
2. *The modality gap is orthogonal to the span of image embeddings and text embeddings, and image embeddings and text embeddings have zero mean in the subspace orthogonal to the modality gap.*

Cross-modal Transferability under Modality Gap. The above findings with respect to the geometry of the modality gap indicate that the classifier input between training and cross-modal evaluation only differs in a constant $\boldsymbol{g}$, i.e., $h(\boldsymbol{x}) \approx h(\boldsymbol{y} + \boldsymbol{g})$. Intuitively, since the modality gap $\boldsymbol{g}$ is an orthogonal constant to the span of embeddings, the weight matrix of the learned classifier should also be orthogonal to $\boldsymbol{g}$. Hence the prediction of the classifier is not affected by $\boldsymbol{g}$. This intuition explains why we observe strong cross-modal transferability under modality gap in practice, across different multi-modal contrastive models trained on different datasets. These results are presented in Section A.2. In Appendix C.1, we further theoretically prove that a linear classifier trained with a regularized quadratic loss is *guaranteed* to be orthogonal to the modality gap and hence achieves cross-modal transferability.

Cross-modal Transferability by Closing the Modality Gap. The observation that the modality gap approximates a constant provides us another perspective to achieve cross-modal transferability — by closing the modality gap so that there is no inconsistency when feeding embeddings from another modality. We propose a simple technique to close the modality gap. During training, instead of feeding $\boldsymbol{x}$ to the model h, we feed it with $\boldsymbol{x} - \mathbb{E}_{\boldsymbol{x}}[\boldsymbol{x}]$. During cross-modal evaluation, we feed $\boldsymbol{y} - \mathbb{E}_{\boldsymbol{y}}[\boldsymbol{y}]$ instead of $\boldsymbol{y}$. With this strategy, we close the gap and observe additional improvements in cross-modal transferability compared to training with the gap.

2.2 Diagnosing vision models using language

Having established that text embeddings can be good proxies for image embeddings (Section 2.1 and A.2), we now describe DrML, which uses natural language inputs for diagnosing vision classifers.

Discovering Error Slices through Language. Deep learning models often make systematic errors on subgroups of inputs with similar attributes, referred to as *error slices* and formally defined as:

$$\mathbb{S} = \{\mathcal{S} \subseteq \mathcal{X} | e(\mathcal{S}) \gg e(\mathcal{X})\},$$

where $\mathcal{X}$ is a test set of images and $e(\cdot)$ is the model's error rate on the set of input images. However, collecting a large enough test set that covers different image distributions is a fundamental challenge. The collected test set often only covers a small percentage of model failure modes (i.e., error slices) in the wild. In contrast, language inputs are easy to generate.

Our proposed method, DrML, is capable of discovering error slices through language inputs. DrML works as follows: 1) We define an *attribute set* $\mathcal{A}$ related to the task; 2) Given a specific attribute subset $\mathcal{F} \subseteq \mathcal{A}$, we use different prompt generators $p \in \mathcal{P} : 2^{\mathcal{A}} \mapsto \mathcal{Y}$ to map attribute combinations to text inputs. In this way, we can combine a wide range of attributes with different prompts to collect a diverse and novel set of text inputs. The generated text set $\mathcal{Y}$ is typically much more diverse than the available image test set $\mathcal{X}$, allowing the discovery of more comprehensive and unseen error slices.

Importantly, DrML has two distinctive benefits over the typical approach of using an image test set. First, DrML only requires minimal effort to define a meaningful set of attributes to generate the input set, circumventing the human cost of data collection. Second, the combination of defined attributes naturally defines human-interpretable data slices, whereas image-based slice discovery methods do not directly provide a text summary of the error slice.

Identifying Influential Attributes through Language. Interpreting what attributes influence model predictions is crucial for understanding why models fail. Since language is directly interpretable by humans, we perform counterfactual analysis using language to understand which attributes or concepts most impact model predictions. With $\mathcal{A}$ defined as the attribute set, we aim to identify a subset of attributes that significantly influences model predictions to any given class c:

$$\mathbb{A}_c = \{a \in \mathcal{A} | s_c(a) \gg 0\},$$

where $s_c(\cdot)$ is the *influence* of an attribute to class c. We measure the influence by Shapley value, which computes average prediction change with the presence and absence of this attribute:

$$s_c(a) = \sum_{\mathcal{F} \subseteq \mathcal{A} \setminus \{a\}} \frac{|\mathcal{F}|!(|\mathcal{A}| - |\mathcal{F}| - 1)!}{|\mathcal{A}|!} (p_c(\mathcal{F} \cup \{a\}) - p_c(\mathcal{F})),$$

where $p_c(\cdot)$ is the average predicted probability of class c on a set of inputs with certain attributes.

With natural language, we can easily compose a large set of inputs with and without that attribute and feed them to the model to calculate the influence. For example, to compute the influence of attribute "ocean" on class "waterbird", we can generate various text inputs such as "A photo of *species* on the ocean" and "A photo of *species*", and compute the average difference of the model predicted probabilities of "waterbird". Note that it is particularly challenging to identify influential attributes using image inputs because it requires an extensive collection of images with attribute annotations.

2.3 Rectifying Vision Model Misbehaviors using Language

In addition to model diagnosis, our finding also allows us to further rectify vision classifiers through language. Based on cross-modal transferability, we propose a simple method that continues to train the vision model using synthesized text slices.

Given the error slices $\mathbb{S} = \{\mathcal{S} \subseteq \mathcal{X} | e(\mathcal{S}) \gg e(\mathcal{X})\}$ discovered, we aim to rectify model performances on these error slices by minimizing $|\mathbb{S}|$. For each $\mathcal{S} \in \mathbb{S}$, we generate a large set of natural language inputs related to this slice $\mathcal{Y}_{\mathcal{S}}$ through attribute composition and prompt manipulation, and continue training the model on these inputs $\mathcal{Y}_{\mathcal{S}}$.

3 Conclusion

Our work reveals a valuable advantage of using vision classifiers built on top of multi-modal embedding spaces learned through contrastive learning – the ability to diagnose and rectify the vision classifiers using natural language inputs. We first use a combination of theoretical analysis and experimental findings to verify that cross-modal transferability exists; namely, that text inputs can act as good proxies for image inputs. This then allows us to propose and validate a framework for diagnosing and rectifying vision classifiers using natural language inputs. Our work suggests promising new directions both for achieving reliable and trustworthy computer vision models, and for the use of cross-modal transferability in other problem domains.

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Overview of Appendix

In this appendix, we supplement additional details of experiments, theory, datasets, and baselines.

- In Appendix A, we demonstrate that text embeddings are good proxies for image embeddings in multi-modal contrastive representation space. Based on that, we demonstrate how DrML successfully diagnose and rectify models on three datasets representing three typical errors.
- In Appendix B, we show how our work is related to many works in different fields and we provide a thorough discussion.
- In Appendix C, we provide a theoretical proof of cross-modal transferability given the modality gap, additional cross-modal transferability results on MS-COCO and ImageNet, and the visualization of the modality gap.
- In Appendix D, we provide details of four datasets (MS-COCO, Waterbirds, FairFace, and dSpritesV) used in our experiments, including data preprocessing, attributes, and prompts. We also provide the model and experimental details.
- In Appendix E, we provide two baseline methods. First, we present the result using text-to-image generation for model diagnosis, which sometimes fails to generate fidelity images given text prompts. Second, we present the baseline method for slice discovery using DOMINO, which fails when error slices are absent in the dataset.

A Experiments

In this section, we first demonstrate that text embeddings are good proxies for image embeddings in multi-modal contrastive representation space (Section A.2). Based on that, we demonstrate how DrML successfully discovers error slices (Section A.3), identifies influential attributes (Section A.4), and further rectifies model misbehaviors on three datasets (Section A.5).

A.1 Experimental Details

Model Architecture. We use CLIP (Radford et al., 2021) as the shared multi-modal embedding space. For classifiers built on CLIP's embeddings, we use linear layers and multi-layer perceptrons.

Datasets. For cross-modality transferability (Section A.2), we use the **MS-COCO** dataset (Lin et al., 2014), which includes both captions and object annotations for each image. The task is a multi-label classification problem of predicting the presence of 80 objects based on images or captions. For model diagnosis and rectification, we simulate the three common types of model failures. For *spurious correlation*, we use the **Waterbirds** dataset (Sagawa et al., 2020) which asks a model to classify if a given bird image is a waterbird or a landbird. The training data contains a spurious correlation between bird species and backgrounds — 95% of waterbirds appear in the water, and 95% of landbirds appear on the land. For *underrepresented data*, we use **FairFaces** (Karkkainen & Joo, 2021) which contains face images from 9 age groups and 7 race groups. The task is gender classification. To simulate the underrepresentation of minority groups, we sample races in proportion to the demographics of the state of Montana for our training set. For *unseen data*, we use **dSpritesV** (Matthey et al., 2017) which contains images of shapes with different colors, sizes, and positions. The task is to classify the shape in an image. To simulate errors caused by unseen data, we only use images with orange triangles or green squares during training. More details are shown in the Appendix D.

A.2 Are Text Embeddings Good Proxies for Images Embeddings?

We have provided theoretical explanations in Section 2.1 that a classifier's boundary is transferable across modalities if the modality gap satisfies certain geometric conditions. Here we first verify these conditions and then show empirically that closing the modality gap can improve transferability.

Modality Gap Geometry.

In Table 1, we first show that *the modality gap can be well approximately by a constant vector*. We verify this by computing distributions over $||\boldsymbol{g}||$ (*magnitude*) and $\cos(\boldsymbol{g}, \mathbb{E}_{\boldsymbol{g}}[\boldsymbol{g}])$ (*direction*). For instance, on MS-COCO, the class-level gaps between image and text embeddings extracted from

Model	Magnitude		Direction		Orthog-onality	Center
	Individual	Class	Individual	Class		
CLIP COCO (2021)	1.18 ± 0.03	0.88 ± 0.04	0.70 ± 0.06	0.94 ± 0.04	0.00 ± 0.06	0.00 ± 0.02
CLIP ImageNet (2021)	-	1.00 ± 0.02	-	0.83 ± 0.05	0.00 ± 0.06	0.00 ± 0.03
ConVIRT (2022)	1.22 ± 0.10	-	0.67 ± 0.09	-	0.02 ± 0.10	0.00 ± 0.02
VideoCLIP (2021)	1.35 ± 0.03	-	0.79 ± 0.04	-	0.00 ± 0.06	0.00 ± 0.02
CLASP (2021)	1.33 ± 0.04	-	0.79 ± 0.12	-	0.03 ± 0.13	0.00 ± 0.02

Table 1: **Geometry analysis of modality gap for various multi-modal contrastive representation spaces.** The modality gap approximates a constant vector, indicated by the magnitude and direction distributions. Modality gap is also orthogonal to the span of embeddings from two modalities, and embeddings' centers for both two modalities are zero vectors in the subspace orthogonal to the gap, indicated by the orthogonality and center distributions. Based on our theoretical analysis, these findings suggest that cross-modal transferability is widely established in multi-modal contrastive learning. ± connects mean and standard deviation.

Modality Gap	Model	Evaluation on Image			Evaluation on Text			Consistency$_\uparrow$
		Loss$_\downarrow$	mF1$_\uparrow$	MF1$_\uparrow$	Loss$_\downarrow$	mF1$_\uparrow$	MF1$_\uparrow$	
-	Random	0.6939	0.0655	0.0443	0.6938	0.0696	0.0437	0.8644
Default	Linear	0.0501	0.7276	0.6790	0.1188	0.5642	0.5429	0.9637
	MLP	0.0480	0.7523	0.7158	0.0888	0.6350	0.6135	0.9789
Closing	Linear	0.0498	0.7280	0.6777	**0.0719**	**0.6554**	**0.6168**	**0.9842**
	MLP	0.0483	0.7495	0.7130	**0.0885**	**0.6503**	**0.6358**	**0.9806**

Table 2: **Cross-modal transferability in multi-modal contrastive representation learning.** We train a classifier using CLIP's image embeddings and test the trained classifier using text embeddings on the MS-COCO multi-label classification dataset. Despite the modality gap, classification boundaries learned from one modality are transferable to another modality. Closing the modality gap further improves cross-modal transferability without harm to in-modal evaluation. Notations: mF1 - Micro F1, MF1 - Macro F1, Random - A randomly initialized linear classifier.

CLIP (ViT-B/32) have almost the same magnitude (0.88 ± 0.04) and direction (cosine similarity 0.94 ± 0.04). We then show that *the modality gap is orthogonal to the span of image embeddings and text embeddings, and embeddings have zero mean in the subspace orthogonal to modality gap*. We verify this by computing distributions over $\cos(\boldsymbol{x} - \mathbb{E}_{\boldsymbol{x}}[\boldsymbol{x}], \mathbb{E}_{\boldsymbol{g}}[\boldsymbol{g}])$ (*orthogonality*) and $\mathbb{E}_{\boldsymbol{x}}[\boldsymbol{x} - \boldsymbol{x}^T \boldsymbol{g}' \boldsymbol{g}']_i$ (*center*), where $\boldsymbol{g}' = \mathbb{E}_{\boldsymbol{g}}[\boldsymbol{g}]/\|\mathbb{E}_{\boldsymbol{g}}[\boldsymbol{g}]\|$ and $i \in [d]$. The subscript i denotes indexing the i-th dimension of the vector. This is supported by the near-zero means with low standard deviations in "orthogonality" and "center" columns. Our findings here show that the assumptions required by our theory of cross-modal transferability (Section 2.1) hold true in practice across various datasets and contrastive multi-modal models, suggesting that *cross-modal transferability should be a pervasive phenomenon in multi-modal contrastive learning*.

Cross-modal Transferability. Table 2 shows the image-to-text transfer results on the MS-COCO validation set. Based on our theory, we indeed find that *cross-modality transferability is possible regardless of the modality gap*. For instance, we find that an image-embeddings-trained linear classifier capable of achieving 67.90% macro F1 score can maintain 54.29% macro F1 score using text embeddings as inputs, and the consistency between predictions using images and texts is 96.37%. Similarly, text-to-image transfer is also possible, which is shown in Appendix Table 7. While there exists slight degradation in performance under cross-modal evaluation, the difference in performance is relatively small, and the cross-modal transfer performance is much higher than random classification. The same finding is observed when using multi-layer perceptrons that learn non-linear features. As shown in the bottom half of Table 2, closing the modality gap further improves cross-modal transferability. The linear classifier achieves 9.12%, 7.39%, and 2.05% absolute improvements on micro F1, macro F1, and prediction consistency for image-to-text transfer without harm to in-modality evaluation. The improvements using MLP are smaller but consistent.

Are Generated Language Prompts Good Predictors of Error Slices? Here we further investigate whether our generated language prompts are good predictors of the error rate of a given data slice. We do so by looking at the correlation between performances on *generated* prompts and corresponding

Method	Waterbirds		FairFace		dSpritesV	
	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson
(Base): Gen 1 Image (Prob)	0.5822	0.5608	0.3884	0.3361	0.3059	0.3119
(Base): Gen 20 Images (Prob)	0.6034	0.5938	0.4288	0.5411	0.4557	0.5309
(1): Generate 1 Text for Slice	0.4167	0.4355	0.0801	0.0957	0.6278	0.6723
(2): (1) + Use Label Probability	0.5899	0.5773	0.2065	0.1760	**0.7071**	0.7481
(3): (2) + Prompt Engineering	**0.6462**	**0.6721**	**0.5669**	0.7024	**0.6998**	0.7595
(Ours): (3) + Prompt Ensemble	**0.6465**	**0.6776**	**0.5614**	**0.7227**	**0.7028**	**0.7918**

Table 3: **Correlation analysis of model performance on image and text slices.** Correlation can be improved by using label probability instead of label accuracy on text predictions, generating better text through prompt engineering and ensemble. Our approach outperforms the baseline text-to-image generation model by a large margin. The best or near-best results are bolded.

image slices. A strong correlation indicates that we can perform error slice discovery using text as proxies, which circumvents the challenges of collecting image data.

We treat each attribute subset $\mathcal{F} \subseteq \mathcal{A}$ as a slice. For each slice, we generate a set of text inputs $\mathcal{Y}_{\mathcal{F}}$ using prompt generators $\mathcal{P}$ and select all the images $\mathcal{X}_{\mathcal{F}}$ with attributes $\mathcal{F}$. We compute the Spearman and Pearson correlation between model performances on $\mathcal{Y}_{\mathcal{F}}$ and $\mathcal{X}_{\mathcal{F}}$. Table 3 shows strong correlation between image and text slices. Furthermore, correlation can be improved by: 1) using the average probability of the label on text predictions instead of accuracy, 2) generating better text inputs via prompt engineering which composes attributes into a more fluent sentence, and 3) prompt ensemble that uses different prompts to generate more diverse inputs (details in Appendix D).

As baselines for comparison, we use the state-of-the-art text-to-image generation model (Rombach et al., 2022) $t : \mathcal{Y} \mapsto \mathcal{X}$ to generate a set of (we use 1 or 20 in our experiment) images $\mathcal{X}'_{\mathcal{F}}$ from text prompts $\mathcal{Y}_{\mathcal{F}}$ and compute correlations between $\mathcal{X}'_{\mathcal{F}}$ and $\mathcal{X}_{\mathcal{F}}$. Our method outperforms this baseline by a large margin and does not utilize significant computational time and cost typically required for the image generation process. Samples of the generated image samples are shown in Appendix E. Even while significant progress has been made in text-to-image generation, generating high-fidelity images that maintain the original semantics is still challenging.

In summary, combining the empirical findings presented in this section and the theoretical results in Section 2.1, we show that text inputs can act as good proxies for image inputs, enabling us to diagnose vision classifiers using generated language prompts.

A.3 Discovered Error Slices

The strong correlation between the performances on text and image slices allows us to confidently run image slice discovery algorithm using text inputs. In this study, we use a simple error slice discovery method of sorting slices by their performances. We further marginalize attributes by merging similar slices into larger slices. In Table 4, we summarize the most essential discovered error slices by our language-based approach on the three datasets, each representing one of the three typical model failure patterns under distribution shifts (Wiles et al., 2022).

For **Waterbird**, the top identified error slices are waterbirds in land and landbirds in water, which correctly corresponded to errors are caused by *spurious correlations* present in the dataset. For **FairFace**, the African American population is among the top identified error slice, which also reflects their *underrepresentation* in our training set. For **dSpitesV**, our method correctly identifies green triangles and orange square as critical error slices. Additionally, pink triangle slices are also correctly identified, since they were *never seen* in the training data. By using images to verify our discovered slices, our method not only correctly identifies the most critical error slices but also accurately predicts the slice performances on images.

In Appendix E, we report results from the state-of-the-art slice discovery baseline DOMINO (Eyuboglu et al., 2022). When evaluated using datasets with the same distribution as the training set, DOMINO can only discover slices present in the dataset, and could not discovery errors caused by distribution shifts.

Waterbirds			FairFace			dSpritesV		
Slice	Text	Image	Slice	Text	Image	Slice	Text	Image
Wbird in L	**0.3258**	**0.3233**	**Black**	**0.9134**	**0.8997**	**Green triangle**	**0.1641**	**0.0616**
Lbird in W	**0.7029**	**0.6524**	Indian	0.9268	0.9446	**Orange square**	**0.2990**	**0.0337**
Wbird in W	0.9306	0.9549	Asian	0.9305	0.9381	**Pink triangle**	**0.5044**	**0.9861**
Lbird in L	0.9957	0.9979	White	0.9427	0.9597	Red triangle	0.5651	0.9954

Table 4: **Discovered error slices using language.** With the images used for validation, our method succeeds in discovering important error slices (bolded) and accurately predicts model performances on image slices. Notations: Image - model accuracy using real image inputs, Text-predicted accuracy using text inputs as a proxy, W - water, L - land.

A.4 Identified Influential Attributes

In Table 5, we report the most influential attributes to a specific class on the same three datasets. These attributes provide a high-quality interpretation of how models predict and why they fail. For example, one of the most influential attributes for waterbird classification is “ocean" with an influence value of 0.3062, indicating that the *model predicted probability of waterbird increases by 0.3* on average when “ocean" is present in a bird image. Since the attribute “place" should not affect predictions, this shows an obvious error of the model. Similar findings apply to the attribute “color" for dSpitesV. But what is more interesting is that the color “pink" is *never seen* during training but will bias the model to predict “square" with 0.1 increased probability. On FairFace, no attribute is found to significantly influence model prediction; thus, no obvious spurious correlations were learned.

Waterbirds (waterbird)			FairFace (female)			dSpritesV (triangle)		
	Attribute	Influence		Attribute	Influence		Attribute	Influence
Place	Ocean	0.3062	**Age**	Very old	0.0229	**Color**	Orange	0.3736
	Lake natural	0.0713		Young	0.0161		Red	-0.0470
	Forest broadleaf	-0.1540		Little	-0.0079		Pink	-0.1181
	Bamboo forest	-0.1931		Infant	-0.0171		Green	-0.3321

Table 5: **Identified the top 2 most positively and negatively influential attributes using language.** These attributes provide insights into how models predict and why they fail.

A.5 Rectified Model Misbehaviors

In Table 6, we report performances of original models and rectified models. On both Waterbirds and FairFace dataset, our simple method of continue training the model on text inputs significantly improves model performances on error slices with minor influences on other slices. We also perform ablation by only training the model on all the language inputs from scratch, and find that continuing to train the pre-trained image model achieves better results, but even training only with language can also work reasonably.

Our approach rectifies model misbehaviors caused by spurious correlation and underrepresented data by correcting the data bias. Another series of methods to tackle these errors are robust training techniques, such as GroupDRO (Sagawa et al., 2020), which explicitly optimizes each slice's performance during training. While GroupDRO performs similarly to ours, it requires attribute annotations on images, which is highly time-consuming and cost-prohibitive for most real-world applications. Moreover, GroupDRO cannot fix errors on unseen data, while ours can.

B Related Work & Discussion

Multi-modal Contrastive Learning. Many recent works in vision-language contrastive learning, such as CLIP (Radford et al., 2021), ALIGN (Jia et al., 2021), and Florence (Yuan et al., 2021), have leveraged large image-caption datasets to obtain embedding spaces that capture rich visual and textual features. As a result, the learned image and text encoders are demonstrated to be strong uni-modal classifiers. In this work, we show how vision models obtained through multi-modal contrastive learning offer another significant advantage — model diagnosis and rectification.

Waterbirds					FairFace				
Slice	Original	Rectify	Lonly	GDRO	Slice	Original	Rectify	Lonly	GDRO
Wbird in L	0.3233	0.5564	**0.5639**	0.7368	**Black**	0.8997	**0.9075**	0.8920	0.9017
Lbird in W	0.6524	**0.8271**	0.7747	0.8155	Asian	0.9381	**0.9390**	0.9290	0.9384
Wbird in W	0.9549	**0.9700**	0.9023	0.9474	Indian	**0.9446**	0.9439	0.9301	0.9453
Lbird in L	**0.9979**	0.9893	0.9443	0.9443	White	0.9597	**0.9626**	0.9424	0.9588

Table 6: **Rectified model performances on discovered error slices.** We continue training models on language inputs corresponding to error slices (bolded) and observe significant performance improvements on these slices. Notations: Lonly - training from scratch with only language inputs of all the slices, GDRO - GroupDRO (not directly comparable because attribute annotations on images are required), W - water, L - land.

Multi-modal Contrastive Representation Space Geometry. Although multi-modal contrastive learning minimizes the distance between embeddings for matched pairs, prior work has shown that embeddings from two modalities are distinctively separated in the embedding space, which is referred to as modality gap (Liang et al., 2022). In this work, we further analyze the geometry of the modality gap and connect it to the cross-modal transferability phenomenon. Our finding is related to several recent works built on multi-modal contrastive representation spaces, such as DALL-E 2 (Ramesh et al., 2022), ClipCap (Mokady et al., 2021), and several other models (Cohen et al., 2022; Gal et al., 2022). They found that trained models can directly take cross-modal embeddings but are worse than taking same-modal embeddings. We not only explain this but provide a straightforward solution to improve transferability, which can be applied to all future works built upon multi-modal embeddings.

Slice Discovery. Many recent works aim to understand model systematic errors by finding subsets of inputs with similar characteristics where the model performs significantly worse. This is referred to as slice discovery (Chung et al., 2019; Singla et al., 2021; d'Eon et al., 2022; Eyuboglu et al., 2022; Jain et al., 2022a). However, these algorithms fail to address the most fundamental challenge for slice discovery — the lack of data. These works are only able to find errors that exist in the dataset. Our work circumvents the data challenge by performing slice discovery on the text space.

Interpretation. Many model interpretation methods have been proposed, including attribution-based (Ribeiro et al., 2016; Lundberg & Lee, 2017; Shrikumar et al., 2017) and concept-based (Ghorbani et al., 2019b; Koh et al., 2020). While these methods help in understanding the model prediction process, the outputs are complicated for humans to understand and inconsistent across models and algorithms (Ghorbani et al., 2019a; Jain et al., 2022b). Others require modifications in model architectures or complex post-processing of model outputs (Ghorbani et al., 2019b; Koh et al., 2020). In contrast, language is inherently understandable by humans and simple to construct. In this work, we interpret the model prediction process by identifying the most influential attributes using language, which provides us meaningful interpretations without pre-processing or post-processing.

Algorithm Fairness. Ensuring algorithmic fairness is key to avoiding potential harm to our society (Hovy & Spruit, 2016; Zou & Schiebinger, 2018). Methods for improving the fairness of machine learning algorithms is an ongoing active area of work (Bolukbasi et al., 2016; Sagawa et al., 2020; Sohoni et al., 2020; Ramaswamy et al., 2021; Liu et al., 2021). Among these, a notable solution is to correct for bias within data, as model bias stems from data bias. In this work, we show that language can be used to correct data bias by generating additional data, hence improving model fairness.

Limitations. While our work introduces a novel and effective approach for diagnosing and rectifying visual classifiers, there are additionally important areas for future work. First, since we assume vision classifiers are built using an image-text embedding space trained through multi-modal contrastive learning, our method can also inherit limitations from the contrastive model and pre-training dataset. For example, although we aim to leverage large and general-purpose image-caption datasets in pre-training, the encoders may still not appropriately embed out-of-distribution examples far from what the contrastive model was trained on. Misaligned or inaccurate pre-training data can also affect encoder quality. Additionally, it is challenging to diagnose low-level visual attributes that are difficult to describe in words, such as texture or object orientation (Leclerc et al., 2021). We consider these fruitful directions for future work. Our method will also benefit from improvements in multi-modal contrastive pre-training as these methods are improved.

C Cross-modal Transferability

C.1 Theoretical Proof for Cross-Modal Transferability

In this section, we expand and formally discuss what is in section 2.1. We theoretically explain the intriguing cross-modal transferability phenomenon. We explain why the modality gap in the multi-modal representation space does not prevent cross-modal transferability because of the unique geometry of the modality gap.

For class $c \in [|\mathcal{C}|]$, let $\boldsymbol{e}_c \in \{0,1\}^{|\mathcal{C}|}$ be a one-hot vector such that the c-th dimension is 1 and other dimensions are 0. We define the following balanced target label vector $\tilde{\boldsymbol{e}}_c := \boldsymbol{e}_c - \mathbb{E}_{c'}[\boldsymbol{e}_{c'}]$, where the expectation is over the distribution of classes on the image domain.

We consider learning a linear function $h_W(\boldsymbol{u}) = \boldsymbol{W}\boldsymbol{u}$, where $\boldsymbol{W} \in \mathbb{R}^{|\mathcal{C}| \times d}$ is the weight matrix and $\boldsymbol{u} \in \mathbb{R}^d$ is the image or text embedding. Given $h_W(\boldsymbol{u})$ and a label c, we consider the following quadratic loss:

$$\mathcal{L}_{\text{quad}}(h_W(\boldsymbol{u}), c) = \|h_W(\boldsymbol{u}) - \tilde{\boldsymbol{e}}_c\|_2^2.$$

The following proposition shows that when the gap between image and caption embeddings is the same for all image-caption pairs and is orthogonal to the embedding span for each modality, a linear model trained to minimize the quadratic loss on one modality transfers to the other modality without loss of accuracy.

Proposition C.1. *Suppose there exists a gap vector $\boldsymbol{g} \in \mathbb{R}^d$ such that every pair of image embedding $\boldsymbol{x}$ and caption embedding $\boldsymbol{y}$ satisfies $\boldsymbol{g} = \boldsymbol{x} - \boldsymbol{y}$. Suppose the gap $\boldsymbol{g}$ is orthogonal to the span of image features (i.e., $\boldsymbol{g}^T\boldsymbol{x} = \boldsymbol{g}^T\boldsymbol{x}'$ for two image embeddings $\boldsymbol{x}$ and $\boldsymbol{x}'$), and the image features have zero mean in the subspace orthogonal to $\boldsymbol{g}$ (i.e., $\mathbb{E}_x[\Pi_g(\boldsymbol{x})] = \boldsymbol{0}$ where $\Pi_g(\boldsymbol{x})$ projects the vector $\boldsymbol{x}$ to the subspace orthogonal to $\boldsymbol{g}$). Then, for any $\lambda > 0$ and linear function $h_W(\boldsymbol{u})$ that minimizes the regularized quadratic loss $\mathbb{E}_{x,c}[\mathcal{L}_{quad}(h_W(\boldsymbol{x}), c)] + \lambda\|\boldsymbol{W}\|_F^2$, we have that*

$$\mathbb{E}_{x,c}[\mathcal{L}_{quad}(h_W(\boldsymbol{x}), c)] = \mathbb{E}_{y,c}[\mathcal{L}_{quad}(h_W(\boldsymbol{y}), c)].$$

Thus, cross-modal transferability happens.

Proof of Proposition C.1. Since $\boldsymbol{g}^T\boldsymbol{x} = \boldsymbol{g}^T\boldsymbol{x}'$ for all image features $\boldsymbol{x}$ and $\boldsymbol{x}'$, we can find a $\tau \in \mathbb{R}$ such that $\boldsymbol{x} = \Pi_g(\boldsymbol{x}) + \tau\boldsymbol{g}$. Notice that

$$\begin{aligned}
\mathbb{E}_{x,c}[\mathcal{L}_{\text{quad}}(h_W(\boldsymbol{x}), c)] &= \mathbb{E}_{x,c}[\|\boldsymbol{W}\boldsymbol{x} - \tilde{\boldsymbol{e}}_c\|_2^2] \\
&= \|\mathbb{E}_x[\boldsymbol{W}\boldsymbol{x}] - \mathbb{E}_c[\tilde{\boldsymbol{e}}_c]\|_2^2 + \mathbb{E}_{x,c}[\|(\boldsymbol{W}\boldsymbol{x} - \tilde{\boldsymbol{e}}_c) - (\mathbb{E}_x[\boldsymbol{W}\boldsymbol{x}] - \mathbb{E}_c[\tilde{\boldsymbol{e}}_c])\|_2^2] \\
&= \|\mathbb{E}_x[\boldsymbol{W}\boldsymbol{x}] - \mathbb{E}_c[\tilde{\boldsymbol{e}}_c]\|_2^2 + \mathbb{E}_{x,c}[\|\boldsymbol{W}\Pi_g(\boldsymbol{x}) - \tilde{\boldsymbol{e}}_c\|_2^2] \\
&= \|\boldsymbol{W}\mathbb{E}_x[\Pi_g(\boldsymbol{x})] + \tau\boldsymbol{W}\boldsymbol{g} - \mathbb{E}_c[\tilde{\boldsymbol{e}}_c]\|_2^2 + \mathbb{E}_{x,c}[\|\boldsymbol{W}\Pi_g(\boldsymbol{x}) - \tilde{\boldsymbol{e}}_c\|_2^2].
\end{aligned}$$

Since $\mathbb{E}_x[\Pi_g(\boldsymbol{x})] = \boldsymbol{0}$ and $\mathbb{E}_c[\tilde{\boldsymbol{e}}_c] = \boldsymbol{0}$, the first term reduces to $\tau^2\|\boldsymbol{W}\boldsymbol{g}\|_2^2$. Notice that the second term in the loss decomposition only involves $\boldsymbol{W}$'s components that are orthogonal to $\boldsymbol{g}$. Thus the minimization of the second term is independent of the minimization of the first term. As a result, any $\boldsymbol{W}$ that minimizes the regularized quadratic loss must satisfy $\boldsymbol{W}\boldsymbol{g} = \boldsymbol{0}$.

For a pair of image and text features $\boldsymbol{x}, \boldsymbol{y}$, since $\boldsymbol{x} - \boldsymbol{y} = \boldsymbol{g}$ and $\boldsymbol{W}\boldsymbol{g} = \boldsymbol{0}$, we have $h_W(\boldsymbol{x}) = h_W(\boldsymbol{y})$. Hence we know their quadratic losses must be the same, which finishes the proof. □

C.2 Additional Cross-modal Transferability Results

MS-COCO. In the main paper, we only report image-to-text transfer, where we train a classifier on image embeddings and test on text embeddings. Here we report the full results, including text-to-image transfer, in Table 7.

Model	Transfer	In-Modal Evaluation				Cross-Modal Evaluation				Consistency$_\uparrow$
		M	Loss$_\downarrow$	mF1$_\uparrow$	MF1$_\uparrow$	M	Loss$_\downarrow$	mF1$_\uparrow$	MF1$_\uparrow$	
Random	-	$\mathcal{I}$	0.6939	0.0655	0.0443	$\mathcal{T}$	0.6938	0.0696	0.0437	0.8644
Default Modality Gap										
Linear	$\mathcal{I} \rightarrow \mathcal{T}$	$\mathcal{I}$	0.0501	0.7276	0.6790	$\mathcal{T}$	0.1188	0.5642	0.5429	0.9637
	$\mathcal{T} \rightarrow \mathcal{I}$	$\mathcal{T}$	0.0580	0.6983	0.6631	$\mathcal{I}$	0.1572	0.5320	**0.4833**	0.9527
MLP	$\mathcal{I} \rightarrow \mathcal{T}$	$\mathcal{I}$	0.0480	0.7523	0.7158	$\mathcal{T}$	0.0888	0.6350	0.6135	0.9789
	$\mathcal{T} \rightarrow \mathcal{I}$	$\mathcal{T}$	0.0572	0.7119	0.6826	$\mathcal{I}$	0.0750	0.6359	0.5929	0.9795
Closing Modality Gap										
Linear	$\mathcal{I} \rightarrow \mathcal{T}$	$\mathcal{I}$	0.0498	0.7280	0.6777	$\mathcal{T}$	**0.0719**	**0.6554**	**0.6168**	**0.9842**
	$\mathcal{T} \rightarrow \mathcal{I}$	$\mathcal{T}$	0.0578	0.6988	0.6628	$\mathcal{I}$	**0.0660**	**0.5782**	0.4767	**0.9858**
MLP	$\mathcal{I} \rightarrow \mathcal{T}$	$\mathcal{I}$	0.0483	0.7495	0.7130	$\mathcal{T}$	**0.0885**	**0.6503**	**0.6358**	**0.9806**
	$\mathcal{T} \rightarrow \mathcal{I}$	$\mathcal{T}$	0.0573	0.7073	0.6763	$\mathcal{I}$	**0.0685**	**0.6603**	**0.6173**	**0.9801**

Table 7: **Cross-modal transferability in multi-modal contrastive representation learning.** We train a classifier using CLIP's image embeddings and test the trained classifier using text embeddings, vice versa, on the MS-COCO multi-label classification dataset. Despite the modality gap, classification boundaries learned from one modality are transferable to another modality. Closing the modality gap further improves cross-modal transferability without harm to in-modal evaluation. Notations: $\mathcal{I}$ - Image, $\mathcal{T}$ - Text, M - Modality, mF1 - Micro F1, MF1 - Macro F1, Random - A randomly initialized linear model.

ImageNet. In the main paper, we report cross-modal transferability on the MS-COCO dataset. Here we report cross-modal transferability results using the ImageNet dataset (Deng et al., 2009). We split ImageNet validation set into 40K / 10K images for training / evaluation. We apply OpenAI CLIP's 80 prompts to 1000 ImageNet class names and get 80K texts, and we split them into 64K / 16K for training / evaluation. All the experimental settings are the same as MS-COCO experiments. Results are shown in Table 8.

Again, despite the modality gap, we find that the classification boundaries learned from one modality are transferable to the other modality. When a linear classifier is trained on image embeddings and achieves 70.86% image classification accuracy, directly feeding the text embeddings to the trained classifier achieves 85.24% accuracy. The transfer from text to image is much worse than from image to text, because the texts we used are generated from prompts and thus lack diversity to train a classifier with good decision boundaries. Closing the modality gap improves the transferability in most cases.

Split	Image-to-Text		Text-to-Image	
	Linear	MLP	Linear	MLP
Default Modality Gap				
In-Modal Evaluation	0.7086	0.6687	0.9974	0.9951
Cross-Modal Evaluation	0.8524	0.7758	0.4953	**0.4552**
Closing Modality Gap				
In-Modal Evaluation	0.7048	0.6683	0.9978	0.9949
Cross-Modal Evaluation	**0.8754**	**0.7892**	**0.5050**	0.4438

Table 8: **Cross-modal transferability in multi-modal contrastive representation learning using the ImageNet dataset.** We split ImageNet validation set 50K images to 40K / 10K for training and evaluation. Texts are generated using OpenAI's 80 prompts multiply by 1000 class names.

C.3 Modality Gap

Figure 2 shows the modality gap phenomenon in various multi-modal contrastive learning models, where inputs from two modalities are embedded at arm's length in their shared representation space. This phenomenon is caused by the combined effect of model initialization and optimization. Deep neural networks have the cone effect — encoders will only map inputs to a small cone of the entire representation space. Therefore, two cones will be created for a multi-modal model with two encoders.

As a sequence, the modality gap occurs at the initialization stage. During optimization, the contrastive loss will preserve the gap due to mismatched data (Liang et al., 2022).

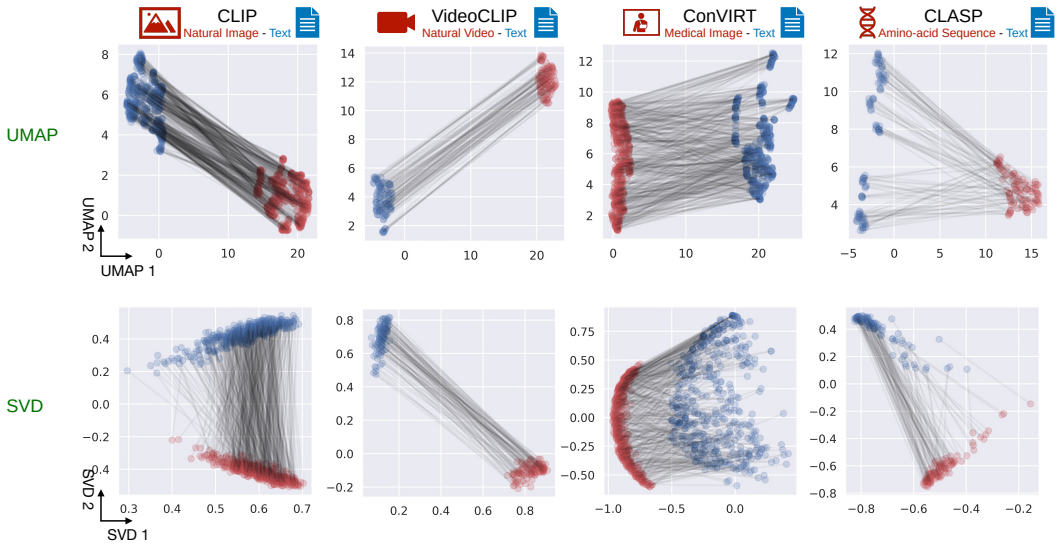


Figure 2: **Modality gap for multi-modal contrastive learning.** Embeddings from two modalities are visualized using UMAP and SVD. Figure credit: Liang et al. (2022).

D Datasets and Experimental Details

In this section, we report details of four datasets: MS-COCO (Lin et al., 2014), Waterbirds (Sagawa et al., 2020), FairFace (Karkkainen & Joo, 2021), and dSpritesV (Matthey et al., 2017), and details of two major experiments.

D.1 Data Pre-processing

MS-COCO. We follow the standard MS-COCO dataset split, which includes 118K / 5K images for training / validation. Each image is annotated with multiple objects from 80 categories and five human-written captions. We randomly select one caption from five captions. Therefore, we have 118K / 5K image-caption pairs with multiple labels for training / validation.

Waterbirds. We follow the standard Waterbirds dataset split, which includes 4.8K / 1.2K images for training / validation. Data samples can be viewed in Figure 5 and 6.

FairFace. We resample the training set using the demographics from the state of Montana, which includes 92.8% White, 6.4% Indian, 0.5% Asian, and 0.3% Black. The final dataset contains 17K / 11K images for training / validation. Data samples can be viewed in Figure 5 and 6.

dSpritesV. We use our own scripts to reproduce a variant of the dSprites dataset and name it dSpritesV. We use six colors (red, pink, orange, green, cyan, blue), four locations (upper left, upper right, lower left, lower right), and three sizes (small, medium, large) to create triangles and squares with a scale ranging from 0.8 to 1.2. Each attribute is uniformly sampled, and we synthesize 10K images. We only use 80% orange triangle and 80% green square for training. Finally, it has 1.3K / 8.7K images for training / validation. Data samples can be viewed in Figure 5 and 6.

D.2 Attributes

Waterbirds. Two attributes are used: species (200 values) and places (4 places).

FairFace. Three attributes are used: races (7 values), ages (9 values), and genders (2 values).

dSpritesV. Three attributes are used: colors (6 values), size (3 values), and shapes (2 values).

D.3 Prompt Engineering

Waterbirds. We use "{species}, {place}." as the raw prompt, and "a photo of a {species} in the {place}." as the engineered prompt. Therefore, we can generate $200 \times 4 = 800$ text inputs.

FairFace. We use "{age adjective}, {race}, {gender}." as the raw prompt, and "a photo of a {race} {age adjective} {gender}." as the engineered prompt. Therefore, we can generate $7 \times 9 \times 2 = 126$ text inputs. The age adjectives are infant (0-2), little (3-9), teenage (10-19), young (20-29), adult (30-39), middle-aged (40-49), senior (50-59), elderly (60-69), and very old (more than 70).

dSpritesV. We use "{size}, {color}, {shape}." as the raw prompt, and "{size} {color} {shape}." as the engineered prompt. Therefore, we can generate $3 \times 6 \times 2 = 36$ text inputs.

D.4 Prompt Ensemble

We use OpenAI CLIP's 80 prompts (Radford et al., 2021) to augment text inputs by 80 times. Parts of them are shown in Figure 3.

D.5 Experimental Details

Model Details. Unless explicitly stated, we use CLIP (ViT-B/32) for all experiments, encoding images and texts in the same 512-dimensional space. Linear layer maps input dimension 512 to the number of classes. Multi-layer perception uses the hidden size as 512.

Cross-modal Transferability Training Details. For each image-caption pair, we use CLIP's image and text encoder (Radford et al., 2021) to get its image embedding and text embedding. We do not use image augmentation techniques during training and inference. We train the linear model or multi-layer perception for 25 epochs using the Adam optimizer with a fixed learning rate of 0.001. During training, CLIP's image and text encoder are fixed. We pick the best model based on the lowest validation loss on the training modality.

Classifiers Training Details. For each image in the dataset, we use CLIP's image encoder (Radford et al., 2021) to get its image embedding. We do not use image augmentation techniques during training and inference. We train the linear model or multi-layer perception for 25 epochs using the Adam optimizer with a fixed learning rate of 0.001. During training, CLIP's image encoder is fixed. We pick the best model based on the lowest validation loss on images.

Model Rectification Training Details. For each text from error slices generated by attribute composition and prompt engineering, we use CLIP's text encoder (Radford et al., 2021) to get its text embedding. We continue training the pre-trained linear model or multi-layer perception for 10 epochs using the Adam optimizer with a fixed learning rate of 0.001. During training, CLIP's text encoder is fixed. We pick the best model based on the lowest validation loss on texts.

E Baselines

E.1 Language-based Vision Model Diagnosis Baseline: Text-to-Image Generation

In Figure 4, we show the baseline method to diagnose vision models using language — text-to-image generation. The method generates real images to test models using the text-to-image generation model.

From the results, we can understand why this baseline is worse than our method, which does not require explicitly generating images. While significant progress has been made in the text-to-image generation field, state-of-the-art text-to-image generation models (Rombach et al., 2022) still fail to generate fidelity images.

In addition, text-to-image generation is computationally expensive, requiring thousands of more computations than our approach.

E.2 Error Slice Discovery Baseline: DOMINO

In Figure 5 and 6, we show the discovered error slices using the baseline slice discovery method, DOMINO (Eyuboglu et al., 2022).

In real-world applications, it is unrealistic to assume a large set of labeled images from different distributions is available. Therefore, the most critical challenge for slice discovery is *data*. In this work, we circumvent the data challenge by using language to synthesize extensive test examples.

Overview of Contributions

In summary, our contributions are:

1. We present a theoretical explanation of when cross-modal transferability happens (Section 2.1), and empirically verify that the assumptions required by the analysis is true in practice across a range of multi-modal contrastive models and datasets (Section A.2).
2. We propose DrML, a framework for diagnosing vision models using natural language, including error slice discovery and influential attribute identification. We empirically validate DrML by simulating common types of failure modes using the Waterbirds (Sagawa et al., 2020), FairFace (Karkkainen & Joo, 2021), and dSpitesV (Matthey et al., 2017) datasets, and show the effectiveness of our method in identifying known error slices and influential attributes.
3. We further demonstrate that DrML can rectify undesirable model behaviors and improve model performance with respect to the identified error slices and influential attributes, by fine-tuning the vision classifier using text embeddings constructed from the diagnosis process.

Ethics Statement

One of the main contributions of our work is an approach for diagnosing and rectifying vision classifiers trained using embeddings from a multi-modal contrastive model. We showcase experimental results on identifying error slices and influential attributes. For example, our method can detect failures caused by the lack of representation of certain races in the training set. In our FairFace experiments, the prediction of gender (i.e., the label "female") given an image was affected by race (e.g., the race "black"). We further show that we can rectify this behavior using our approach. Hence, we see our work as a contribution to the broader community concerned with model accountability and model auditing, and to improving the responsible integration of AI into society.

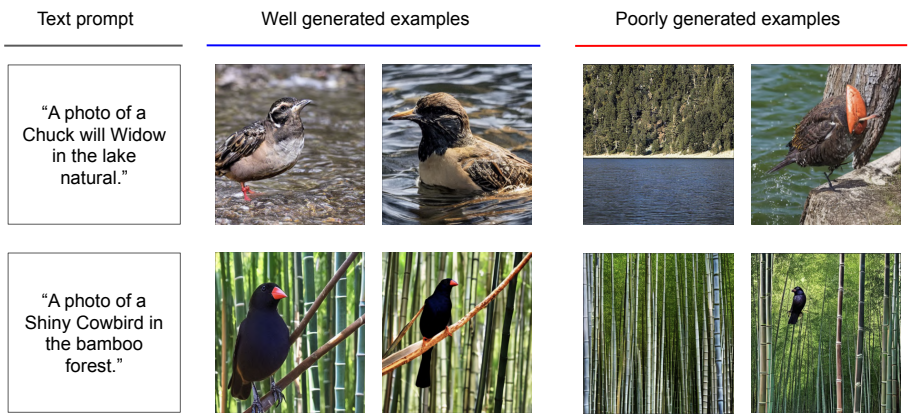
However, it is also important to be aware of potential negative impacts brought about by our findings. One can imagine an adversary who extends our approach and uses it to their advantage, perhaps reinforcing racial or gender biases by fine-tuning a vision model using biased language prompts. Our work also inherits limitations from the contrastive model and pre-training datasets used to obtain the image and text encoders, as described in the Discussion section of our paper. We hope that this statement raises awareness both of the importance of better model diagnosis and rectification methods and of future directions of work to address limitations and potential negative impacts.

Reproducibility Statement

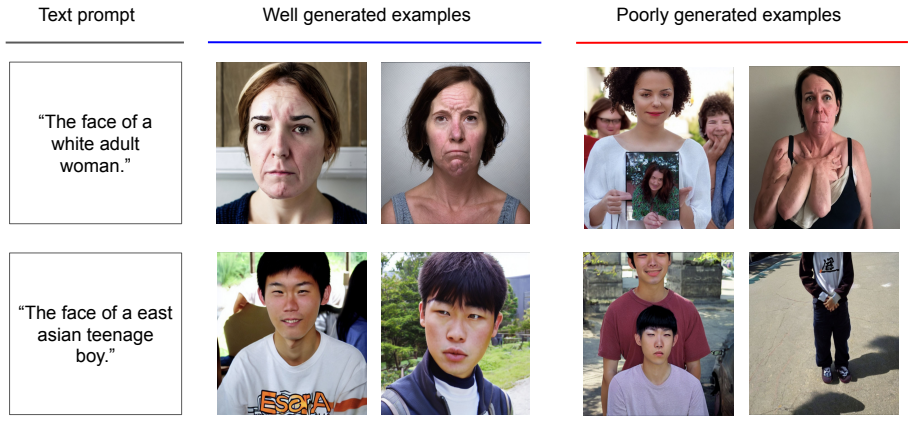
We provide open-source implementation of our work at `https://anonymous.4open.science/r/diagnosis/`. The implementations will enable researchers to reproduce all the experiments described here as well as run their own analyses on additional multi-modal models and datasets.

```
openai_imagenet_template = [
    lambda c: f"a bad photo of a {c}.",
    lambda c: f"a photo of many {c}.",
    lambda c: f"a sculpture of a {c}.",
    lambda c: f"a photo of the hard to see {c}.",
    lambda c: f"a low resolution photo of the {c}.",
    lambda c: f"a rendering of a {c}.",
    lambda c: f"graffiti of a {c}.",
    lambda c: f"a bad photo of the {c}.",
    lambda c: f"a cropped photo of the {c}.",
    lambda c: f"a tattoo of a {c}.",
    lambda c: f"the embroidered {c}.",
    lambda c: f"a photo of a hard to see {c}.",
    lambda c: f"a bright photo of a {c}.",
    lambda c: f"a photo of a clean {c}.",
    lambda c: f"a photo of a dirty {c}.",
    lambda c: f"a dark photo of the {c}.",
    lambda c: f"a drawing of a {c}.",
    lambda c: f"a photo of my {c}.",
    lambda c: f"the plastic {c}.",
    lambda c: f"a photo of the cool {c}.",
    lambda c: f"a close-up photo of a {c}.",
    lambda c: f"a black and white photo of the {c}.",
    lambda c: f"a painting of the {c}.",
    lambda c: f"a painting of a {c}.",
    lambda c: f"a pixelated photo of the {c}.",
    lambda c: f"a sculpture of the {c}.",
    lambda c: f"a bright photo of the {c}.",
    lambda c: f"a cropped photo of a {c}.",
    lambda c: f"a plastic {c}.",
    lambda c: f"a photo of the dirty {c}.",
    lambda c: f"a jpeg corrupted photo of a {c}.",
    lambda c: f"a blurry photo of the {c}.",
    lambda c: f"a photo of the {c}.",
    lambda c: f"a good photo of the {c}.",
    lambda c: f"a rendering of the {c}.",
    lambda c: f"a {c} in a video game.",
    lambda c: f"a photo of one {c}.",
    lambda c: f"a doodle of a {c}.",
    lambda c: f"a close-up photo of the {c}.",
    lambda c: f"a photo of a {c}.",
    lambda c: f"the origami {c}.",
    lambda c: f"the {c} in a video game.",
    lambda c: f"a sketch of a {c}.",
    lambda c: f"a doodle of the {c}.",
    lambda c: f"a origami {c}.",
    lambda c: f"a low resolution photo of a {c}.",
    lambda c: f"the toy {c}.",
    lambda c: f"a rendition of the {c}.",
    lambda c: f"a photo of the clean {c}.",
    lambda c: f"a photo of a large {c}.",
    lambda c: f"a rendition of a {c}.",
    lambda c: f"a photo of a nice {c}.",
    lambda c: f"a photo of a weird {c}.",
    lambda c: f"a blurry photo of a {c}.",
    lambda c: f"a cartoon {c}.",
    lambda c: f"art of a {c}.",
    lambda c: f"a sketch of the {c}.",
    lambda c: f"a embroidered {c}.",
    lambda c: f"a pixelated photo of a {c}.",
]
```

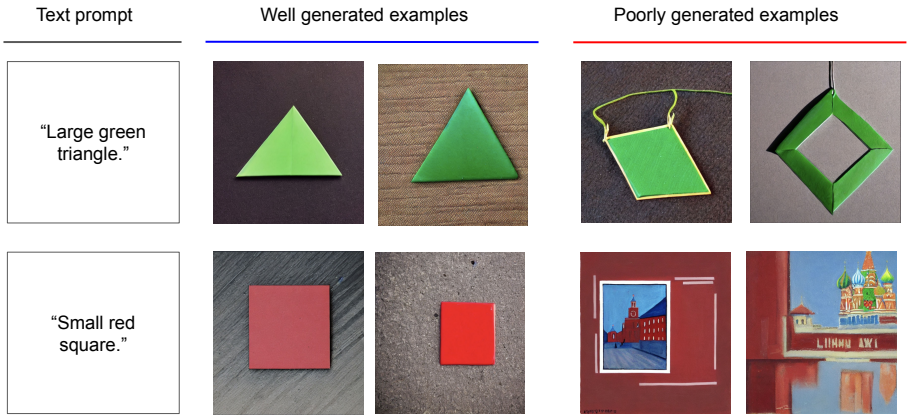
Figure 3: A subset of the 80 prompts form OpenAI we use to augment text inputs for prompt ensembling.



Well-generated examples (columns 2-3) are realistic and correctly reflect the bird species and background location described in the text prompts. Poorly generated images either do not include the bird species (column 4) or are noticeably unnatural (column 5). Specifically, the top image in column 5 includes a bird with lobster claws as its head — a rather unusual phenomenon in the real world

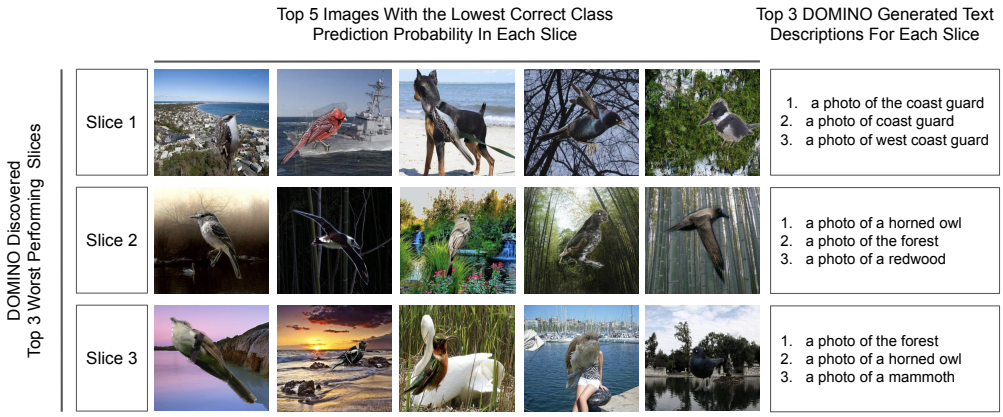


Well-generated examples (columns 2-3) are realistic and correctly reflect the ethnicity and age group described in the text prompts. Poorly generated images include more than one person (column 4), do not include the person's face (column 5 bottom), or are noticeably unrealistic (column 5 top). For instance, the top image in column 5 includes a woman with arms protruding out of her chest, which is rare in the real world.

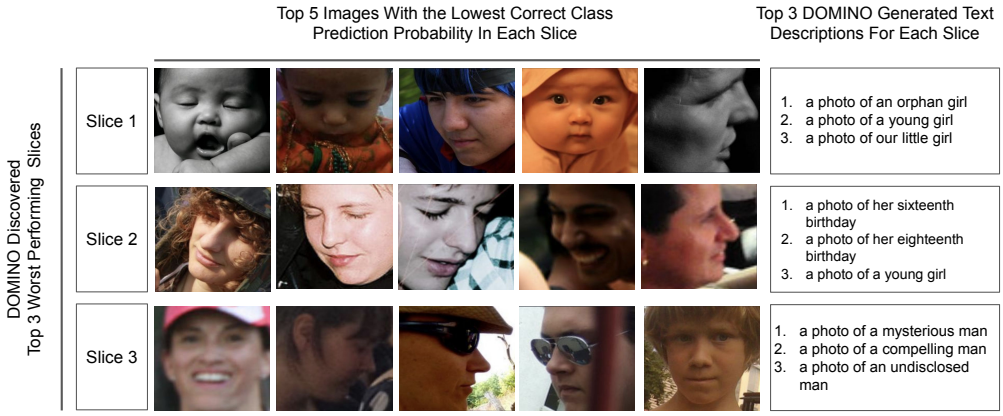


Well-generated examples (columns 2-3) correctly reflect the shape and color described in the text prompt. Poorly generated images either include incorrect shapes (column 4-5 top) or are misinterpreted due to polysemy (column 4-5 bottom). For instance, the phrase "red square" was misinterpreted by our model as a historic site in Moscow.

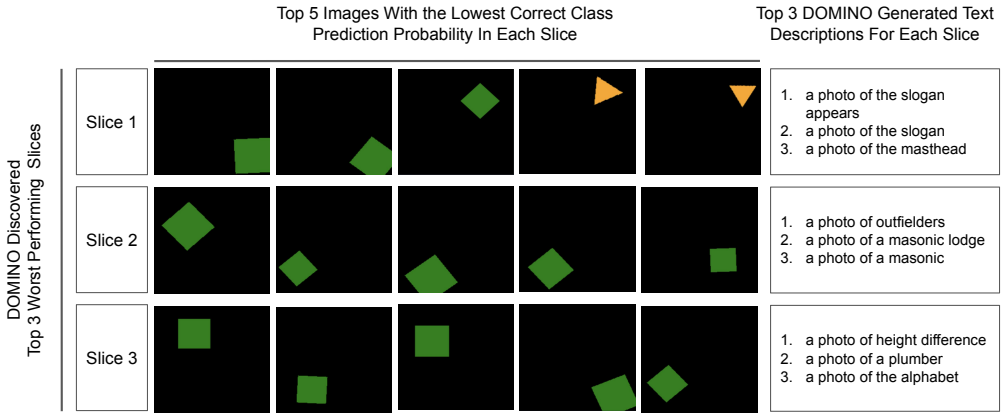
Figure 4: Text-to-image generation results on Waterbirds, FairFace, and dSpitesV using the state-of-the-art generation model (Rombach et al., 2022).



For in-distribution Waterbird, the text descriptions generated from DOMINO do not elucidate which attributes are causing misclassifications. In addition, some of the descriptions are incorrectly generated. For instance, "coast guards" are not present in any of the photos in Slice 1.

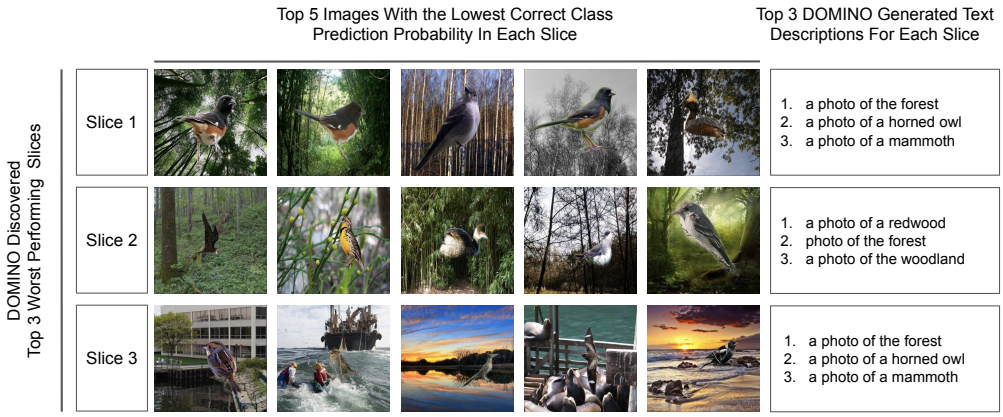


For in-distribution Fairface, DOMINO is unable to discover the correct error slices. Instead of slices for minority groups, DOMINO discovered slices for the prevalent ethnic group in the dataset. Furthermore, the generated descriptions failed to include the key attribute — race.

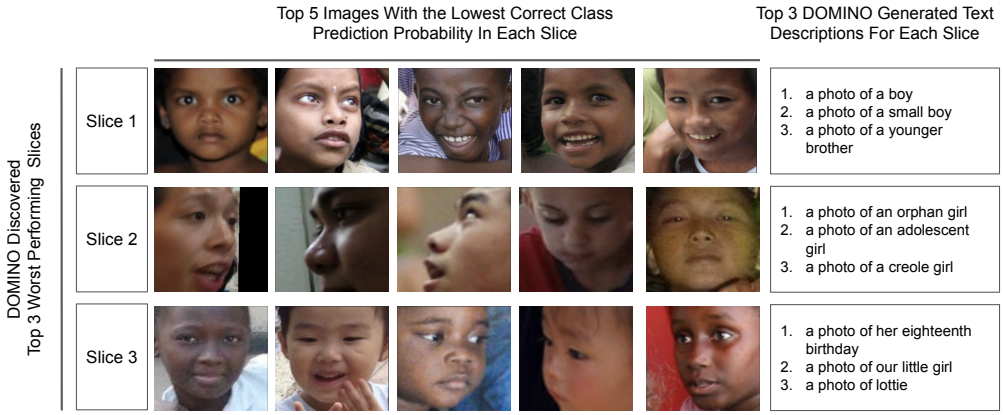


For in-distribution dSpritesV, DOMINO failed to discover the most critical error slices - slices with spurious correlations (orange squares & green triangles) and slices with unseen data (pink triangle). The generated descriptions also do not reflect images in the slices.

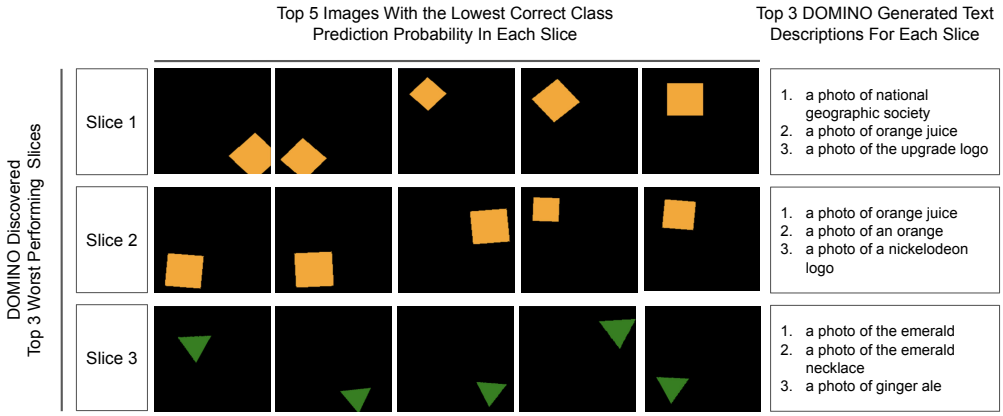
Figure 5: Discovered error slices on **in-distribution** Waterbirds, FairFace, and dSpitesV datasets using the state-of-the-art slice discovery method DOMINO (Eyuboglu et al., 2022). DOMINO is unable to discover most of the top error slices. The generated text descriptions often do not reflect images in the slice accurately.



For out-of-distribution Waterbird, DOMINO was unable to generate text that clearly defines the source of misclassification for each slice. Moreover, the some of the descriptions do not accurately describe the images. For example, "mammoths" are never included in any images.



For out-of-distribution Fairface, DOMINO is able to discover the some correct error slices. However, the generated descriptions failed to provide any insights as to why the model fail for these slices. Specifically, the generated descriptions do not include keywords for the race attribute.



For out-of-distribution dSpritesV, DOMINO is able to discover slices with spurious correlation (orange squares & green triangles). However, the generated text descriptions do not include attributes that contribute to the spurious correlation. Additionally, DOMINO did not discover slices with unseen data (pink triangles).

Figure 6: Discovered error slices on **out-of-distribution** Waterbirds, FairFace, and dSpitesV datasets using the state-of-the-art slice discovery method DOMINO (Eyuboglu et al., 2022). DOMINO was able to capture some, but not all, error slices. Furthermore, artificially generating out-of-distribution data for evaluation remains challenging in real-world settings.