Chroma-VAE: Mitigating Shortcut Learning with Generative Classifiers

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Abstract

Deep neural networks are susceptible to shortcut learning, using simple features to achieve low training loss without discovering essential semantic structure. Contrary to prior belief, we show that generative models alone are not sufficient to prevent shortcut learning, despite an incentive to recover a more comprehensive representation of the data than discriminative approaches. However, we observe that shortcuts are preferentially encoded with minimal information, a fact that generative models can exploit to mitigate shortcut learning. In particular, we propose Chroma-VAE, a two-pronged approach where a VAE classifier is initially trained to isolate the shortcut in a small latent subspace, allowing a secondary classifier to be trained on the complementary, shortcut-free latent subspace. In addition to demonstrating the efficacy of Chroma-VAE on benchmark and real-world shortcut learning tasks, our work highlights the potential for manipulating the latent space of generative classifiers to isolate or interpret specific correlations.

1 Introduction

As science fiction writer Robert Heinlein quipped in his 1973 novel *Time Enough for Love*, progress is made not by "early risers", but instead by "lazy men trying to find easier ways to do something". Indeed, we can accuse modern machine learning models of emulating the same behaviour. There are notable examples of models that wind up learning the wrong things. For example, images of cows standing on anything other than grass fields are commonly misclassified, because the combination of cows and grass fields is so prevalent in training data that the model simply learns to rely on the background as a predictive signal [4]. A more concerning example involves predicting pneumonia from chest X-ray scans. Hospitals in the training data have differing rates of diagnosis, a fact that the model easily exploits by learning to detect hospital-specific metal tokens in the scans rather than signals relevant to pneumonia itself [50].

Deep neural networks can learn brittle, unintended signals under empirical risk minimization (ERM) [11, 16, 13], a well-known phenomenon observed and studied by various communities. These signals often possess two key attributes: (i) they are *spuriously correlated* to the label and are therefore strongly predictive [6, 48, 29], despite having no meaningful semantic relationship with the label, and (ii) they are learnt by the neural network as a result of its *inductive biases* [41, 10]. A recent unifying effort by Geirhos et al. [10] coins the term *shortcut* to describe such a signal. Networks that learn shortcuts will fail to generalize to relevant or challenging distribution shifts.

Prior work has sought to alleviate this problem under various formalizations, most commonly in the settings of group robustness [e.g. 37, 26, 7] or adversarial robustness [e.g. 5, 43]. In this paper, we motivate a different approach to mitigate undesirable shortcuts, where we seek instead to learn a *shortcut-invariant representation* of the data — that is, "everything but the shortcut". To this end, we first observe empirically that deep neural networks preferentially encode shortcuts as they are

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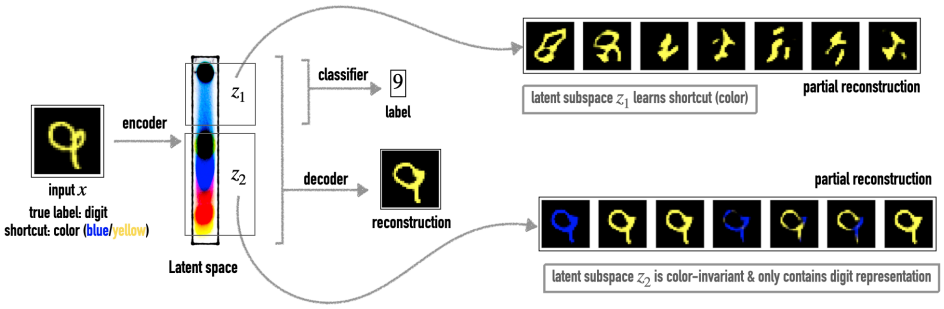


Figure 1: A visual representation of Chroma-VAE. The latent space is partitioned into two subspaces, one of which is incentivized to encode the shortcut under ERM. The complementary subspace learns a shortcut-invariant representation.

the most efficient compression of the data that is strongly predictive of training labels. This helps to explain why shortcut learning is so prevalent amongst discriminative classifiers.

However, this same preference can be exploited in a *generative* classifier to learn a shortcut-invariant compression. Specifically, we consider the Variational Auto-Encoder (VAE) [22], capable of learning latent representations of the data. Our key insight is to back-propagate the classifier's loss through a latent *subspace*, while reconstructing with the *entire latent space*. The model minimizes classification error by encoding the shortcut in this subspace. Since the shortcut representation is isolated, the complementary subspace is free to learn a shortcut-invariant representation through reconstruction. The final classifier is then trained on this invariant representation. We dub our approach **Chroma-VAE**, inspired by the technique of chromatography, which separates the components of a chemical mixture travelling through the mobile phase. Figure 1 summarizes our approach.

Our contributions are as follows:

- We show empirically that: (i) deep neural networks preferentially encode shortcuts as the most efficient compression (Section 3.1), and (ii) the shortcut representation can be sequestered in a latent subspace of the VAE classifier (Section 3.2).
- These observations allow us to propose Chroma-VAE (Section 3.3), an approach designed to learn a classifier on a shortcut-invariant representation of the data. We demonstrate the effectiveness of Chroma-VAE on several benchmark and real-world datasets (Section 5).

2 Background and Notation

Even though shortcuts are present in many domains within deep learning [4, 48, 2, 32, 28, 12], we restrict our discussion to image classification tasks, as (i) VAEs are widely applied to modeling image distributions, and (ii) shortcut learning is ubiquitous in the vision domain.

Let $\mathcal{D}_{tr} = \{\mathbf{x}_i, y_i\}_{i=1}^N$ denote i.i.d. training data. A variational auto-encoder (VAE) [22] (E_ϕ, D_θ) models $\mathbf{x}$ with a latent variable: $p(\mathbf{x}, \mathbf{z}) = p(\mathbf{z})p(\mathbf{x}|\mathbf{z})$. The prior $p(\mathbf{z})$ is typically $\mathcal{N}(\mathbf{0}, I)$ and the likelihood $p(\mathbf{x}|\mathbf{z})$ is implicitly modeled by the decoder network $D_\theta(\mathbf{z}) = \big(\mu_\theta(\mathbf{z}), \text{diag}\left(\sigma^2_\theta(\mathbf{z})\right)\big)$ as $\mathcal{N}\big(\mathbf{x}|\mu_\theta(\mathbf{z}), \text{diag}\left(\sigma^2_\theta(\mathbf{z})\right)\big)$. Maximizing $p(\mathbf{x})$ is intractable due to the integral over $\mathbf{z}$. Instead, we use an encoder network $E_\phi(\mathbf{x}) = \Big(\mu_\phi(\mathbf{x}), \text{diag}\left(\sigma^2_\phi(\mathbf{x})\right)\Big)$ as an (amortized) variational approximation $q_\phi\big(\mathbf{z}|\mu_\phi(\mathbf{x}), \text{diag}(\sigma^2_\phi(\mathbf{x}))\big)$ and maximize the Evidence Lower BOund (ELBO):

$$\text{ELBO}(\theta, \phi, \mathbf{x}) := \mathbb{E}_{\mathbf{z}\sim q_\phi}\left[\log \frac{p_\theta(\mathbf{x}, \mathbf{z})}{q_\phi(\mathbf{z}|\mathbf{x})}\right] \tag{1}$$

by computing unbiased estimates of its gradients.

In a hybrid VAE classifier $(E_\phi, D_\theta, C_\varphi)$, we model $\mathcal{D}_{tr}$ as $p(\mathbf{z}, \mathbf{x}, y) = p(\mathbf{z})p(\mathbf{x}|\mathbf{z})p(y|\mathbf{x})$. $p(y|\mathbf{x})$ is modeled by a classifier network C_φ that takes the latent mean $\mu_\phi(\mathbf{x})$ as input and outputs class

probabilities, i.e. $p_{\varphi,\phi}(y|\mathbf{x}) = \mathrm{CE}\Big(y, C_\varphi\big(\mu_\phi(\mathbf{x})\big)\Big)$, where CE is the cross-entropy loss. Again, maximizing $p(\mathbf{x}, y)$ is intractable and the training objective is:

$$\mathcal{L}(\theta, \phi, \varphi) := -\sum_{\mathbf{x},y\in\mathcal{D}_{tr}} \mathrm{ELBO}(\theta, \phi, \mathbf{x}) + \lambda \cdot \log p_{\varphi,\phi}(y|\mathbf{x}) \tag{2}$$

where λ is a scalar multiplier widely used in practice to account for the fact that $p(\mathbf{x})$ is typically magnitudes larger than $p(y|\mathbf{x})$ on image datasets.

Group Terminology Let $s \in \mathcal{S}$ denote the shortcut (spurious) label. The *group* of an input $\mathbf{x}$ is $g = (s, y)$, the combination of its shortcut and true labels. *Majority groups* refer to examples with the dominant correlation between s and y on the training data, while *minority groups* refer to the small number of examples with the opposite correlation that ERM models typically misclassify. *Group robustness* refers to the ability of models to generalize to distribution shifts where shortcuts are no longer predictive. Methods to improve group robustness can make use of group annotations, however, our method *does not assume access* to group labels at train or test time.

3 Chroma-VAE: Separating Shortcuts Generatively

The key intuition behind our approach is to exploit shortcut learning for representation learning, by using a VAE to learn a shortcut-invariant representation of the data. Two central ideas, supported by empirical observations, motivate our method: (i) deep neural networks preferentially encode shortcuts under finite and limited representation capacity, and (ii) the shortcut representation can be sequestered in a latent *subspace* of the VAE when jointly trained with a classifier.

3.1 Shortcuts are preferentially encoded under limited representation capacity

Why do shortcuts exist? As Geirhos et al. [10] note, shortcuts arise because the model's inductive biases (the sum total of interactions between training objective, optimization algorithm, architecture, and dataset) favour learning certain patterns over others, e.g. convolutional neural networks (CNNs) prefer texture over global shape [3, 9].

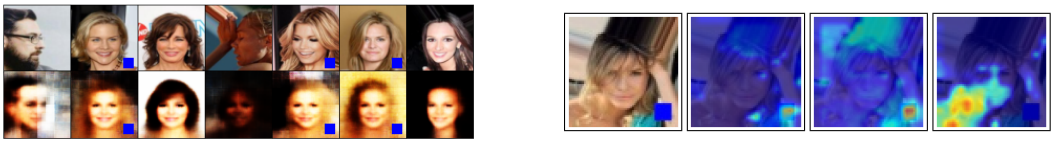
We approach this from an information-theoretic lens. Deep neural networks are commonly thought of as representation learners that optimize the information bottleneck (IB) trade-off, i.e. they aim to learn a maximally compressed representation (minimally sufficient statistic) that fits the labels well [45, 40]. Our key empirical observation is that in datasets where shortcuts exist, **they are often efficiently compressed, and the compressed information is predictive of labels**. As such, deep models preferentially encode shortcuts, especially under limited representation capacity.

We consider an experiment on the `CelebA` dataset [27], where the task is predicting hair colour ("blond" or not). We inject a synthetic shortcut in the form of a 10×10 blue "patch", superimposed onto the image with 0.9 probability for the positive class (see Figure 2b). We first train a discriminative classifier on the labels, and then *independently* learn a decoder on the (fixed) hidden layer of the trained discriminative model.

Figure 2a shows the reconstructions of the decoder. The shortcut is accurately replicated in sharp detail where it exists, but other regions of the reconstructions are not as faithful to the originals. In particular, note that reconstructions are even less accurate for examples of the positive class (with the shortcut). Since the decoder was learned separately, this implies that the classifier's latent compression primarily encoded for the shortcut's presence.

This result is further supported by visualizing the activated regions of the input images during training. We implement Grad-CAM [39], which computes a linear combination of activation maps weighted by the gradients of output logits (or any upstream parameters). This can be visualized as a heatmap superimposed on the original image, showing regions of the image with the greatest positive contributions to the network's prediction.

In Figures 2b-e, we visualized these heatmaps on models with a bottleneck hidden layer of different sizes. As we can see, the smaller the bottleneck size, the stronger the activations on the shortcut patch. With additional model capacity, the model is more likely to encode other relevant (or spurious) features *in addition to* the shortcut itself.



(a) (b) (c) (d) (e)

Figure 2: **(Left) (a)** Examples of reconstructions by a decoder trained independently on the discriminative model's hidden layer. The shortcut is sharply captured where it exists. Reconstruction is particularly poor on images *with* the shortcut — the reconstructed faces seem to collapse to the same archetype that does not resemble the original images. **(Right)** Grad-CAM heatmaps on a `CelebA` test image. **(b)** The original image with the shortcut patch. **(c)-(e)** Averaged activations across all training epochs on three separate models, with a bottlenecked hidden layer of sizes 4, 32, and 128 respectively. The smaller the bottleneck, the more likely it is that the model only focuses on the shortcut patch. With more capacity, the model focuses on other regions of the image.

From these experiments, we see that deep neural networks tend to compress input data in a manner which preserves the shortcut when it is compressible with little information and is simultaneously predictive of training labels. This tendency is exacerbated under limited latent capacity and is the reason why discriminative classifiers are susceptible to shortcut learning under ERM.

3.2 VAE classifiers can sequester shortcuts into specific latent dimensions

What presents a problem for discriminative modeling can be exploited into an advantage using a generative model. The key insight here is that we can train a VAE classifier where the latent space is partitioned into two disjoint subspaces — however, only one subspace feeds into a classifier and is backpropagated through using labels. This subspace encodes the shortcut precisely because this information maximizes the classifier's performance (i.e. simultaneously exhibits high mutual information with the labels and small mutual information with the data). **The remaining subspace therefore encodes a partial representation of the image without the shortcut.**

Formally, we modify the standard VAE classifier described in Section 2 as follow: we partition the latent space as $\mathbf{z} = (\mathbf{z}_1, \mathbf{z}_2)$. The classifier C_φ uses only $\mathbf{z}_1$ as input, i.e. for a given data point $\mathbf{x}$, the predicted output is $C_\varphi\big(\mu_\phi(\mathbf{x})_1\big)$. As such, $\mathbf{z}_1$ is used for both reconstruction and classification, whereas $\mathbf{z}_2$ is used for reconstruction only.

We visualize the results of this experiment in two ways: (i) Grad-CAM, where we use gradient weights both of $\mu_\phi(\mathbf{x})_1$ and of $\mu_\phi(\mathbf{x})_2$, and (ii) sampling **partial reconstructions** $\tilde{\mathbf{x}}$ from the VAE: given an encoding $\mu_\phi(\mathbf{x})$, we replace each half $\mu_\phi(\mathbf{x})_i$ with standard Gaussian noise and sample from the decoder:

$$\tilde{\mathbf{x}}_1 \sim D_\theta\Big(\big[\mu_\phi(\mathbf{x})_1 \quad N(\mathbf{0}, I)\big]^\top \Big) \tag{3}$$

$$\tilde{\mathbf{x}}_2 \sim D_\theta\Big(\big[N(\mathbf{0}, I) \quad \mu_\phi(\mathbf{x})_2\big]^\top \Big) \tag{4}$$

We use the same predictive task and synthetic shortcut as described in Section 3.1. The visualizations are displayed in Figure 3. As can be seen from Figures 3b-c, Grad-CAM shows that $\mu_\phi(\mathbf{x})_1$ is most sensitive to pixels around the blue patch, whereas $\mu_\phi(\mathbf{x})_2$ is sensitive to pixels spread out in other regions of the image (including certain regions of the celebrity's blonde hair). This highlights that the representation of the patch is largely isolated in $\mathbf{z}_1$.

Partial reconstructions in Figures 3d-e support this observation. In Figure 3d, where $\mu_\phi(\mathbf{x})_1$ is fixed and we perturb only $\mathbf{z}_2 \sim N(\mathbf{0}, I)$, the decoded samples $\tilde{\mathbf{x}}_1$ represent a variety of faces that do not resemble the original image. However, *all* samples contain the shortcut patch in the bottom-right corner. Conversely, in Figure 3e where $\mu_\phi(\mathbf{x})_2$ is fixed, the reconstructed samples $\tilde{\mathbf{x}}_2$ greatly resemble the original image, but may or may not contain the shortcut. In other words, $\mu_\phi(\mathbf{x})_1$ is strongly correlated with the shortcut's presence, whereas $\mu_\phi(\mathbf{x})_2$ is *uncorrelated* with the shortcut.

Together, Grad-CAM and the partial reconstructions suggest that the latent representation of the shortcut patch has largely been sequestered into $\mathbf{z}_1$. Intuitively, this is believable — as the classification loss on C_φ only back-propagates through $\mathbf{z}_1$, it will learn representations that are most useful

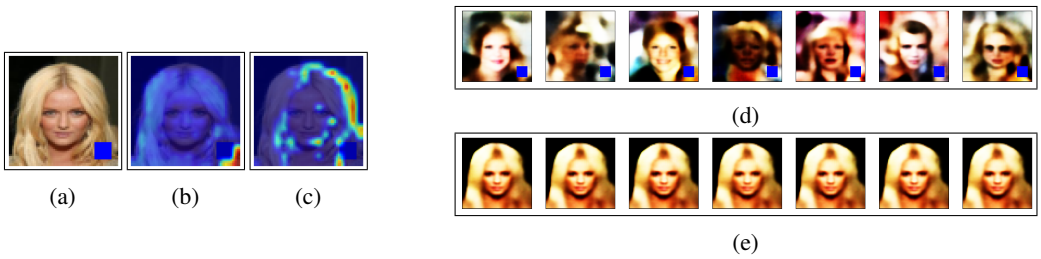


Figure 3: **(a)** Original image containing shortcut. **(b)** Grad-CAM with $\mu_\phi(\mathbf{x})_1$ gradients. **(c)** Grad-CAM with $\mu_\phi(\mathbf{x})_2$ gradients. **(d)** Partial reconstructions $\tilde{\mathbf{x}}_1$. **(e)** Partial reconstructions $\tilde{\mathbf{x}}_2$. While no patches are present in samples of $\tilde{\mathbf{x}}_2$ here, we have observed that they can occur with small probability. Conversely, across our many repeated samplings, the shortcut patch is *always* present in samples of $\tilde{\mathbf{x}}_1$. Note also that $\tilde{\mathbf{x}}_1$ samples contain a variety of hair colours, whereas $\tilde{\mathbf{x}}_2$ samples faithfully reconstruct the celebrity's blonde hair.

Algorithm 1 Chroma-VAE

Input: data $\mathcal{D}_{tr}$, VAE classifier $(E_\phi, D_\theta, C_\varphi)$, $\mathbf{z}_2$-classifier $C^{(2)}_{\varphi'}$, optimization hyperparameters
// Training initial VAE classifier
initialize (θ, ϕ, φ)
using Adam, minimize Equation (2), noting that C_φ only takes $\mu_\phi(\mathbf{x})_1$ as input
// Training $\mathbf{z}_2$-classifier
initialize φ'
compute the (fixed) input $\mu_\phi(\mathbf{x})_2$ using E_ϕ
using Adam, minimize $\mathcal{L}(\varphi') = \text{CE}\Big(y, C^{(2)}_{\varphi'}\big(\mu_\phi(\mathbf{x})_2\big)\Big)$
return $C^{(2)}_{\varphi'}$

for prediction. This representation is dominated by the shortcut patch, as we showed in Section 3.1. Since the model is also simultaneously learning to reconstruct the image, most other information describing the image is partitioned into $\mathbf{z}_2$, resulting in $\tilde{\mathbf{x}}_2$ samples being very similar to the original.

3.3 Chroma-VAE

These results suggest a simple approach: we only need to train a separate, secondary classifier $C^{(2)}_{\varphi'}$ on $\mathbf{z}_2$ **after** the initial VAE classifier $(E_\phi, D_\theta, C_\varphi)$ has been trained, i.e. $\mathbf{z}_2$ is a fixed input into $C^{(2)}_{\varphi'}$ that is not back-propagated through. As shown in Section 3.2, a well-trained VAE classifier learns $\mathbf{z}_2$ in a way that minimizes shortcut representation but also contains other predictive features (by virtue of $\mathbf{z}_2$ learning to reconstruct). As such, $C^{(2)}_{\varphi'}$ will be shortcut-invariant while remaining predictive.

We name this approach **Chroma-VAE**. A full description is provided in Algorithm 1. Our method has two hyperparameters: the dimensionality of $\mathbf{z}$, $\dim(\mathbf{z})$, and the partition fraction, $z_p = \frac{\dim(\mathbf{z}_1)}{\dim(\mathbf{z}_1)+\dim(\mathbf{z}_2)} \in (0, 1)$, which controls the relative sizes of $\mathbf{z}_1$ and $\mathbf{z}_2$.

From here on, we will refer to C_φ as the $\mathbf{z}_1$-classifier ($\mathbf{z}_1$`-clf`; *not* used for prediction) and $C^{(2)}_{\varphi'}$ as the $\mathbf{z}_2$-classifier ($\mathbf{z}_2$`-clf`; shortcut-invariant classifier used for prediction). Since $\mathbf{z}_2$ is a vector, the $\mathbf{z}_2$-classifier need not be a deep neural network. Indeed, we noticed in our experiments that simpler models like k-nearest neighbors can sometimes perform better; see Section 5 for more details.

$\tilde{\mathbf{x}}_2$-classifier As we observed in Section 3.2, the partial reconstructions $\tilde{\mathbf{x}}_2$ are uncorrelated with the shortcut. As such, instead of training $C^{(2)}_{\varphi'}$ on $\mathbf{z}_2$, we can simply generate partial reconstructions and train a classifier on samples of $\tilde{\mathbf{x}}_2$ directly in $\mathcal{X}$-space. This allows us to exploit deep models since the inputs are now images. We term this the $\tilde{\mathbf{x}}_2$-classifier ($\tilde{\mathbf{x}}_2$`-clf`).

4 Related Work

Generative Classifiers Depending on how we decompose $p_\theta(\mathbf{x}, y)$, generative classifiers can be divided into two categories: (i) *class-conditional models* $p_\theta(y)p_\theta(\mathbf{x}|y)$ or (ii) *hybrid models* $p_\theta(\mathbf{x})p_\theta(y|\mathbf{x})$. The majority of previous work on deep generative classifiers [e.g. 38, 52] focus on the former category, e.g. for semi-supervised learning [23, 19] or adversarial robustness [38]. The most notable work in the latter category is Nalisnick et al. [30], which applies hybrid models to OOD detection and semi-supervised learning. Our work uses VAEs as the deep generative component, since we require explicit latent representation. Due to the need to encode specific predictive features (the shortcut) into the latent space, our work focuses on *hybrid* models only.

Group Robustness Out-of-distribution (OOD) generalization is a broad area of study [e.g. 8, 14, 35], depending on what assumptions are made on the relationship between train and test distributions as well as the information known at train time. In this work, we primarily consider distribution shifts arising from the presence of shortcuts or spurious correlations, where signals predictive in the train distribution are no longer correlated to the label in the test distribution. Prior work has generally approached this from the *group robustness* perspective, where the objective is to maximize worst-group accuracy (typically the minority groups) while retaining strong average accuracy. To the best of our knowledge, Chroma-VAE is the first method to tackle shortcut learning from a supervised representation learning approach using generative classifiers.

Methods in this space can be distinguished by the assumptions they make. Some work rely on having group labels for training data [1, 36, 51, 37], for example, Sagawa et al. [36] optimize worst-group accuracy directly. However, as group annotations can be expensive to acquire, other approaches relax this requirement [26, 7, 42, 49, 31]. For example, Liu et al. [26], which we compare to, treat misclassified examples by an initial model as a proxy for minority groups; these samples are up-weighted when training the final model. However, their approach is brittle to hyperparameter choices, requiring group labels on validation data (from the test distribution) for hyperparameter tuning.

Compared to existing work, Chroma-VAE does not require training group labels. Furthermore, we found that Chroma-VAE hyperparameters are not sensitive to groups — results in Section 5 were tuned using *average accuracy* on validation data. We hypothesize the reason for this robustness: the effectiveness of Chroma-VAE depends on (i) the shortcut being successfully isolated in $\mathbf{z}_1$ and (ii) $\mathbf{z}_2$ having sufficient capacity to learn the non-shortcut predictive features. (ii) is achieved by choosing $\dim(\mathbf{z})$ appropriately to ensure good reconstruction — this can be evaluated without group labels. Given such an appropriate $\dim(\mathbf{z})$, most non-extreme values of z_f will ensure that $\mathbf{z}_1$ has enough capacity to encode the shortcut. As such, the $\mathbf{z}_2$-classifier will be shortcut-invariant and can be tuned without needing group labels. Table 1 summarize the group label requirements.

Example	Group-DRO [36]	JTT [26]	Chroma-VAE
Group Labels on Train Data	✓	✗	✗
Group Labels on Validation Data	✓	✓	✓/✗

Table 1: Comparison of group label requirements. While Chroma-VAE can be tuned using validation worst-group accuracy, we have found that tuning for average accuracy suffices.

5 Experiments

In Section 5.1, we present results on the `ColouredMNIST` benchmark, a proof-of-concept which we also use to highlight some key observations and comparisons. In Section 5.2, we present results on two additional benchmark datasets: `CelebA` (gender/hair colour) and `Dominoes` (`MNIST-FashionMNIST`). Finally, in Section 5.3, we demonstrate Chroma-VAE on a real-life problem — namely, pneumonia prediction using chest X-ray scans. In addition, Appendix B.1 contains further results on the `CelebA` synthetic patch proof-of-concept that was presented earlier in Section 3.

Baselines and Metrics Detailed experimental setups are found in Appendix A. For `ColouredMNIST`, we evaluate predictive accuracy on the various test distributions. For the other datasets, we evaluate average and worst-group accuracies. We consider the following baselines:

Method	$\mathcal{D}_{in}$	$\mathcal{D}_{out}$
Theoretical UB	75	75
Invariant	60.8	65.6
Naive-Class	87.8	17.8
Naive-VAE-Class	89.0	13.2
Naive-Independent	89.7	11.4
JTT	63.2	63.8
Chroma-VAE ($\mathbf{z}_1$-clf)	88.8	14.8
Chroma-VAE ($\mathbf{z}_2$-clf)	**70.9**	**70.8**
Chroma-VAE ($\tilde{\mathbf{x}}_2$-clf)	69.3	67.9

Table 2: Predictive accuracies on $\mathcal{D}_{in}$ and $\mathcal{D}_{out}$. Chroma-VAE ($\mathbf{z}_2$-clf) is the best-performing classifier. Note that the best that a digit-only classifier can do is 75% since $p_d = 0.75$ by construction.

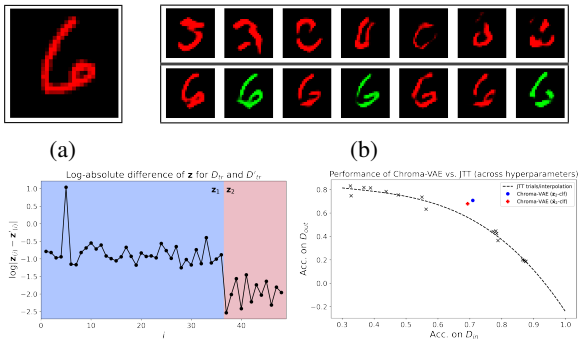


Figure 4: **(a)** Original image. **(b)** Partial reconstructions $\tilde{\mathbf{x}}_1$ *(top row)* and $\tilde{\mathbf{x}}_2$ *(bottom row)*. All samples of $\tilde{\mathbf{x}}_1$ preserve the colour of the original image but not the digit. Conversely, samples of $\tilde{\mathbf{x}}_2$ preserve the digit but can be variably green or red. **(c)** Plot of log-absolute difference for each dimension of $\mathbf{z}$ on $\mathcal{D}_{tr}$ and $\mathcal{D}'_{tr}$. Dimensions of $\mathbf{z}_2$ have smaller differences than $\mathbf{z}_1$. **(d)** Accuracies of various hyperparameter combinations of JTT. We used a polynomial (cubic) regressor to interpolate the accuracy trade-off on $\mathcal{D}_{in}$ and $\mathcal{D}_{out}$; the best point on this curve is reported in Table 2. Both chroma-VAE classifiers lie above this curve.

1. **Naive discriminative classifier** (Naive-Class): ERM classifier
2. **Naive VAE classifier** (Naive-VAE-Class): standard VAE classifier
3. **Naive VAE + classifier** (Naive-Independent): standard VAE is first trained on unlabelled data $\{\mathbf{x}_i\}_{i=1}^N$, the classifier is then separately trained on the latent projection $\{\mu_\phi(\mathbf{x}), y\}_{i=1}^N$
4. **Just Train Twice** (JTT) [26]: classifier is trained with a limited number of epochs, misclassified training points are upweighted and a second classifier is trained again

For fairness, we do not compare to methods that use group labels [36, 34], multiple training environments [1], or counterfactual examples [44].

5.1 ColouredMNIST

We follow the same experimental design as Arjovsky et al. [1]: (i) we first binarize `MNIST` [24] labels $\hat{y}$ (with digits 0-4 and 5-9 as the two classes), (ii) we obtain *actual* labels y (used in training and evaluation) by flipping $\hat{y}$ with probability $p_d = 0.25$, and finally (iii) we obtain colour labels c by flipping y with variable probability p_c, where c is used to colour each image green or red. In the training distribution $\mathcal{D}_{in}$, $p_c = 0.1$, hence colour is the shortcut as c is more strongly correlated to y than $\hat{y}$ is. In the adversarial OOD test distribution $\mathcal{D}_{out}$, $p_c = 0.9$, i.e. every digit is more likely to be shaded the other colour. Note from Table 2 that the invariant classifier (trained on *black-and-white* images) attains similar performance on both $\mathcal{D}_{in}$ and $\mathcal{D}_{out}$, confirming that degraded performance on $\mathcal{D}_{out}$ is solely due to shortcut learning.

The main takeaway from our results in Table 2 is that **Chroma-VAE vastly outperforms all other methods under the adversarial distribution** $\mathcal{D}_{out}$, suggesting that the $\mathbf{z}_2$-classifier is **learning from a largely shortcut-invariant representation** of the data. Accordingly, the $\mathbf{z}_1$-classifier performs just as *poorly* as the naive methods, suggesting the shortcut is heavily present in $\mathbf{z}_1$. This is further confirmed by the partial reconstructions shown in Figure 4b (further examples can be found in Appendix B). Samples of $\tilde{\mathbf{x}}_1$ are colour-invariant whereas samples of $\tilde{\mathbf{x}}_2$ are digit-invariant, suggesting that the bulk of colour representation has been isolated in $\mathbf{z}_1$.

In addition, both the $\mathbf{z}_2$-classifier and $\tilde{\mathbf{x}}_2$-classifier perform well. In particular, we noticed that simpler models work better as the $\mathbf{z}_2$-classifier — MLPs with smaller hidden layers have better accuracies, and our top performance is a k-nearest neighbor classifier with $k = \sqrt{N}$.

Method	CelebA				MF-Dominoes
	Blond/Gender		Attractive/Smiling		
	Ave	Worst	Ave	Worst	Worst
Naive-Class	0.642	0.294	0.625	0.215	0.000
JTT	0.653	0.283	0.647	0.300	
Chroma-VAE ($\mathbf{z}_2$-clf)	**0.820**	**0.544**	**0.669**	**0.531**	**0.840**

Table 3: Average and worst-group test accuracy for the various benchmark tasks. Chroma-VAE beats all the baselines on worst-group accuracy significantly.

(a) (b)

Figure 5: **(a)** `CelebA` example. The original example is **Attractive** but not **Smiling**. All samples of $\tilde{\mathbf{x}}_1$ *(top right)* are not smiling, whereas samples of $\tilde{\mathbf{x}}_2$ *(bottom right)* may or may not be smiling, suggesting that $\mathbf{z}_2$ learns "smile-invariance". **(b)** `MNIST-FashionMNIST` example. $\mathbf{z}_1$ learns the shortcut ("1" digit) and $\mathbf{z}_2$ retains the core feature (shirt image).

As further evidence that the shortcut is represented by $\mathbf{z}_1$, we create $\mathcal{D}'_{tr}$, a dataset that is identical to the training set $\mathcal{D}_{tr}$ except that every image has its colour flipped. We then measure $\log |\mathbf{z}_{(i)} - \mathbf{z}'_{(i)}|$ for every dimension i of the latent space. In Figure 4c, observe that the dimensions of $\mathbf{z}_2$ have a smaller difference than dimensions of $\mathbf{z}_1$, suggesting colour (shortcut) invariance is preserved in $\mathbf{z}_2$.

Next, this experiment highlights our finding that **generative models alone are insufficient.** Neither the VAE classifier (Naive-VAE-Class) nor the independent VAE + classifier (Naive-Independent) improved on the ERM model (Naive-Class). While our work motivated VAEs specifically from observations about the information bottleneck, we note that the community at-large has hoped [10] that *simply* having a generative component might incentivize the model to learn a comprehensive representation of the data-generating factors, and not just the minimum compression necessary for small training loss. Our results show that this is not true. This failure is not limited to hybrid models — further results in Section B.1 show that class-conditional generative classifiers fare just as poorly.

Detailed comparison with JTT JTT has two hyperparameters: (a) the number of epochs T with which the initial classifier was trained, and (b) the factor α by which initially mis-classified examples are upweighted. We tested various combinations of these two hyperparameters (see Appendix A) and Figure 4d shows the results of this ablation. In particular, we can see that while it is possible to choose hyperparameters such that JTT performs better than Chroma-VAE on *one* of the two test distributions, JTT does not outperform Chroma-VAE on *both*.

5.2 Benchmark Datasets

We consider two benchmark `CelebA` tasks: (1) predicting **Blond** where **Gender** is the spurious feature [36, 26], and (ii) predicting **Attractive** where **Smiling** is the spurious feature [25]. We also consider the `MF-Dominoes` dataset [33], where input images consist of `MNIST` digits (0 or 1) concatenated with `FashionMNIST` objects (coat or dress), with the FashionMNIST object being the true label. In all of these experiments, we use the *harder* setting from Lee et al. [25], where the spurious feature is *completely correlated* with the label at train time (by filtering out the two minority groups). Chroma-VAE is naturally suited for this regime, as complete correlation allows the spurious feature to be simultaneously compressible and highly discriminative.

The results are summarized in Table 3. All results were tuned on average accuracy. **Chroma-VAE outperforms the naive discriminative model, as well as JTT,** on both average and worst-group

Method	Ave. Acc.	Worst Acc.
Naive-Class	**85.0**	10.3
JTT	64.2	52.3
Chroma-VAE ($\mathbf{z}_1$-clf)	60.2	47.3
Chroma-VAE ($\mathbf{z}_2$-clf)	59.9	**57.8**

Table 4: Average and worst-group accuracy on the test set.

accuracy. Similarly, the fact that the $\mathbf{z}_1$-classifier does *worse* than a naive discriminative model suggests that the shortcut has been preferentially encoded by $\mathbf{z}_1$. Partial reconstructions for a test example from either dataset, shown in Figure 5, confirm these results.

Detailed Comparison with JTT On the `CelebA` dataset, Table 3 shows that JTT underperformed. This is primarily due to the fact that these experiments are performed in the complete correlation setting (no minority groups). As such, JTT is unable to leverage on misclassification of minority examples to train the final model. This experiment highlights a significant difference between group robustness methods and Chroma-VAE. Group robustness methods like JTT tend to perform more poorly when there fewer minority examples, as they rely on these examples to teach the model what to learn. In contrast, Chroma-VAE leverages representation learning of shortcuts by the classifier. Stronger correlation between the shortcut and true signals means that it is more likely for the shortcut to be preferentially encoded by the VAE classifier, since the shortcut is now a perfect predictor of the label. As such, Chroma-VAE will do better in learning a shortcut-invariant representation.

5.3 Chest X-Rays

We consider the prediction of pneumonia from frontal chest X-ray scans, a well-known example of shortcut learning [50, 34, 20]. The shortcut is the background of the image, which is spuriously correlated with the hospital as different hospitals have different machines, lightning conditions, etc. — resulting in different background artifacts. This poses a problem for datasets containing X-rays from multiple hospitals with differing rates of pneumonia diagnosis.

There is no benchmark dataset and different authors have created their own datasets from existing public or private collections of X-ray repositories. Likewise, we make a training set ($N = 20$K) with roughly equal numbers of X-rays from the National Institutes of Health Clinical Center (NIH) dataset [46] and the Chexpert dataset [18], such that 90% of NIH images are from the negative class and 90% of Chexpert images are from the positive class.

Table 4 shows the results. Examples of partial reconstructions and a qualitative analysis can be found in Appendix B. **The main takeaway from this experiment is that our method is viable on a natural, real-world data set**. Compared to the other approaches, Chroma-VAE has the highest worst-group accuracy. However, we note that it does suffer from lower average accuracy.

6 Discussion and Conclusion

We propose Chroma-VAE, inspired by the empirical observation that shortcuts, being the most efficient and predictive compression of the data, are often preferentially encoded by deep neural networks. Our model makes use of a generative model to train a second classifier on the latent representation of the image where the shortcut is abstracted away. We demonstrate the efficacy of Chroma-VAE on several benchmark and real-world shortcut learning tasks. Finally, we conclude with a few promising avenues for future work:

Learning diverse ensembles with ≥ 2 classifiers In this work, we only considered separating two sets of features (shortcut and true signal). However, Chroma-VAE could be extended to settings where there are multiple relevant predictive features. To this end (and truer to the chromatograph metaphor), Chroma-VAE can be extended to iteratively learn a diverse ensemble of predictors.

Prior on $\mathbf{z}$ Imposing a prior on $\mathbf{z}$ can help to further disentangle the features learnt by $\mathbf{z}_1$ and $\mathbf{z}_2$. One suggestion is to enforce an orthogonal loss component on $\mathbf{z}$, i.e. by minimizing $\langle \nabla_{\mathbf{z}_1} y, \nabla_{\mathbf{z}_2} y \rangle$.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] The experiments in Section 3 and Section 5 support the claims we made.
   (b) Did you describe the limitations of your work? [Yes] Limitations are addressed in experimental findings in Appendix 5.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Potential societal impact of our work is discussed in Section C.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] Section 5 and Appendix A describe the experimental details necessary to reproduce our results. We will release our code accompanying the public release of our paper.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Appendix A.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] We have generally found our results to be robust to repeated random runs.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No] We note that the computational resources we used are typical of most research using the same models and datasets.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] All datasets and models used were cited in Section 5 or Appendix A.
   (b) Did you mention the license of the assets? [No] All these datasets and models are well-known and broadly used. We refer readers to the original papers for licenses.
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   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A] This only applies to `CelebA`, discussed in the original paper.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A] This only applies to `CelebA`, discussed in the original paper.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]