Local Manifold Augmentation for Multiview Semantic Consistency

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Abstract
Multiview self-supervised representation learning roots in exploring semantic consistency across data of complex intra-class variation. Such variation is not directly accessible and therefore simulated by data augmentations. However, commonly adopted augmentations are handcrafted and limited to simple geometrical and color changes, which are unable to cover the abundant intra-class variation. In this paper, we propose to extract the underlying data variation from datasets and construct a novel augmentation operator, named local manifold augmentation (LMA). LMA is achieved by training an instance-conditioned generator to fit the distribution on the local manifold of data and sampling multiview data using it. LMA shows the ability to create an infinite number of data views, preserve semantics, and simulate complicated variations in object pose, viewpoint, lighting condition, background etc.

1 Introduction
With a vision of leveraging massive data for effective visual representation learning, there has been a surging interest in self-supervised learning (SSL). As a prevalent SSL paradigm, multiview self-supervised learning are driven by the goal of learning semantic consistency across data with intra-class variation, which is usually achieved by attracting positive pair of views (Grill et al. 2020; Chen and He 2021; Zhontar et al. 2021; Bardes, Ponce, and LeCun 2022) or meanwhile repelling negative pair of views (Oord, Li, and Vinyals 2018; Chen et al. 2020a; Tian, Krishnan, and Isola 2020; He et al. 2020; Caron et al. 2020). Thanks to the learned invariance to nuisance variation (Ericsson, Gouk, and Hospedales 2021), multiview SSL have shown to yield representations that strongly generalizes to different domains with significant distribution shifts (Mitrovic et al. 2021) and various downstream tasks (Liu, Li, and Sun 2020; Xie et al. 2021; Xiao, Du, and Marlet 2021).

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Figure 1: Comparison of handcrafted augmentation (HCA) and local manifold augmentation (LMA). (a) Visual effect comparison: while HCA leads to simple geometrical and appearance change, LMA consequences more complicated changes, e.g. object pose, viewpoint, lighting condition, background etc. (b) LMA helps MoCov2 to obtain representations that are more invariant to changes in object pose, viewpoint, and illumination.

Therefore, one crucial point in multiview SSL is to access the multiview data with nuisance variation. Such variations are not directly available and therefore are usually simulated with data augmentation techniques such as cropping image patches (Oord, Li, and Vinyals 2018) and changing the color (Tian, Krishnan, and Isola 2020). To this end, effective augmentation strategies have been constructed through a dedicated composition of elementary transformations to provide abundant multiview data and have shown to greatly improve the SSL performance (Chen et al. 2020a,b). Despite so, such a strategy is still limited by the handcrafted opera-
tors which are difficult to design and can hardly simulate complicated nuisance variations such as varied object pose, viewpoint, lighting condition, and background.

Although such complicated variation is challenging to be simulated by handcrafted transformation, it is ubiquitous in the collected datasets. It is quite common that a dataset contains multiple images that depict the same scene or object with varied nuisance factors. These images naturally serve as a valuable source of multiview data with complicated geometrical or appearance changes failed by handcrafted operators but still critical for representation learning.

In this paper, we study extracting the underlying data variation from datasets and construct an augmentation operator named local manifold augmentation (LMA). Straightforward ways to achieve this goal could be regarding the $k$ nearest neighbors ($k$NN) in the dataset as nuisance views and traversing the vicinity in latent space mapped to the whole dataset by generative models (e.g., GAN). However, these methods either suffer from limited views or face the challenge to preserve the semantics of augmented views (Jahanian et al. 2022). Instead, we model distribution on the local manifold of data with an instance-conditioned GAN (IC-GAN) (Casanova et al. 2021) and repurpose it for augmentation. In particular, $k$ nearest neighbors of an image in the dataset are first identified with $k$NN algorithm, and a generator is conditioned on given images and trained to generate images that have a similar appearance to the conditioned images. To this end, the trained generator learns to transform images to their neighbors that vary in some nuisance factors. Since the modeling approach takes advantage of both $k$NN and generative models, LMA instantiated with IC-GAN can create infinite views yet preserve semantics.

Although the multiview data can be significantly enriched by LMA, direct integration of LMA into existing multiview SSL hurts the performance in practice. We analyze that LMA has the potential to reduce the overall quality of training data due to the notorious mode collapse issue of GANs. To mitigate this issue, we apply LMA with a certain probability when introduced into SSL, which ends up with training representation networks on a mixture of real and generated data and preserves the diversity of training data.

Fig. 1 compares the handcrafted augmentation (HCA) and LMA. In contrast to HCA which only leads to simple changes such as crop and color distortion, LMA can consequence more complicated changes in object pose, lighting condition, viewpoint, background etc. (Fig. 1a). We further test the integration of LMA into MoCov2 (Chen et al. 2020b) that requires negative pairs, SimSiam (Chen and He 2021) that does not. Comprehensive experiments on prevalent benchmarks including CIFAR10, CIFAR100, STL10, ImageNet100, and ImageNet show that LMA consistently improves MoCov2 and SimSiam. Furthermore, quantitative evaluations show that the LMA helps to improve the representation invariance to changes in object poses, viewpoints, and illumination (Fig. 1b) and strengthen the representation robustness to various distribution shifts in ImageNet-V2, ImageNet-R, ImageNet Sketch etc.

Our contribution can be summarized as:

1. A novel data augmentation method, named local manifold augmentation (LMA), which can provide more complicated data variation for SSL.

2. A method that integrates LMA into SSL algorithms, which is empirically shown to consistently improve the performance on prevalent benchmarks such as CIFAR10, CIFAR100, STL10, ImageNet100, and ImageNet, and gain more invariant and robust representations.

2 Related Work

2.1 Self-supervised Representation Learning

A rich body of methods devise pretext tasks (Agrawal, Carreira, and Malik 2015; Doersch, Gupta, and Efros 2015; Zhang, Isola, and Efros 2017; Wang, He, and Gupta 2017; Wang and Gupta 2015; Pathak et al. 2016, 2017; Misra, Zitnick, and Hebert 2016; Mahendran, Thewlis, and Vedaldi 2018; Larsson, Maire, and Shakhnarovich 2016; Kim et al. 2018; Jenni and Favaro 2018) where labels come from data itself. In the recent trend of SSL, contrastive learning (Oord, Li, and Vinyals 2018; Tian, Krishnan, and Isola 2020; Chen et al. 2020a; He et al. 2020) becomes one of the most popular approaches and show its great power in learning transferable representations that even outperform supervised one in various transfer learning tasks (He et al. 2020; Chen et al. 2020b). Contrastive learning draws presentations of positive data pairs together and push apart representations of negative pairs, where the positive pairs are usually obtained by applying data augmentation to create two different views of the same data point. More recently, contrasting to negative samples are further proven to be unnecessary by non-contrastive methods (Grill et al. 2020; Chen and He 2021; Zbontar et al. 2021; Bardes, Ponce, and LeCun 2022). In both contrastive and non-contrastive learning methods, invariance with respect to particular transformations, also known as data augmentation, is still a critical motive for SSL algorithms.

2.2 Data Augmentation

Data augmentation is a crucial technique for creating multi-view data in SSL. Low-level image processing operators are employed as data augmentation tools. For example, CPC (Oord, Li, and Vinyals 2018) employs image crops for multi-view data and CMC (Tian, Krishnan, and Isola 2020) takes different color channels of different color-space images as multi-view data. SimCLR (Chen et al. 2020a) first integrates multiple data augmentation including crop, resize, color distortion, Gaussian blurring etc. and empirically show its importance in contrastive learning. The data augmentation pipeline is tuned later which further helps to improve the performance (Chen et al. 2020b). More recently, the data augmentation pipeline is further enriched with multi-crop (Caron et al. 2020) and background removal (Tomasev et al. 2022), which significantly contribute to the improvement of performance. In our work, we also study improving self-supervised representation learning methods with novel data augmentation techniques. In contrast to widely-used ones that are mostly low-level visual transformation, our work attempts to introduce high-level visual transformation that can provide richer multi-view data sources. The most
related work to ours is Jahanian et al. (Jahanian et al. 2022) that creates multi-view data by traversing GAN latent space. Our work differs from it in that we employ a particular GAN for creating multi-view data.

**Steerable GANs** Besides its stunning capability of synthesizing high-fidelity images, the steerable generation of GANs has also attracted a lot of research interests. Earlier works show that smooth transition between images can be obtained with interpolation in the latent space (Goodfellow et al. 2014) and a mixture of ingredients from two images can be obtained by mixing the latent variables (Karras, Laine, and Aila 2019; Karras et al. 2020b). More recent works are more interested in finding ways to manipulate generation to consequence expected changes. One line of works discover the semantic direction in GAN latent space guided by pre-trained attribute classifiers (Abdal et al. 2021; Bau et al. 2018; Nitzan et al. 2020; Patashnik et al. 2021; Shen et al. 2020; Wu, Lischinski, and Shechtman 2021; Yang, Shen, and Zhou 2021). However, these works requires external supervision to discover meaningful directions and therefore do not suit the self-supervised learning setting. Another line of works (Voynov and Babenko 2020; Härkönen et al. 2020; Shen and Zhou 2021; Spingarn-Eliezer, Banner, and Michaeli 2021; Ramesh, Choi, and LeCun 2018; Zhu et al. 2021; Esser, Rombach, and Ommer 2020; Choi et al. 2022) search latent directions without external human supervision. However, it is not guaranteed that the discovered latent manipulation is beneficial to self-supervised representation learning and a recent study shows that random traversal is good enough (Jahanian et al. 2022). Unlike the above works that traverse latent space of GANs, we explore the generation of one particular GAN, i.e., IC-GAN (Casanova et al. 2021), to create data augmentation for SSL learning.

## 3 Method

### 3.1 Multiview Modeling

An implicit visual concept $c$, e.g., a scene or an object, is presented to computers in form of images that probably vary as different views $v(c)$. Multiview representation learning pulls together multiview representations to learn representations $f(c)$ that are invariant to nuisance views, i.e., $f(v(c)) = f(c)$. One challenge is that multiview data is not always available. Existing methods address this issue by transforming a given data point to obtain different views,

$$v(c) = t(i(c)), t \sim \mathcal{T},$$

where $i(c)$ denotes the an image that represent $c$, which is available from the collected dataset, $t$ denotes a particular data transformation sampled from a distribution of transformation $\mathcal{T}$. However, since the transformation is usually constructed by composing a variety of hand-crafted operators, it is difficult to precisely depict the underlying multiview distribution $P(v(c))$.

In this paper, we consider leveraging distribution of local data manifold to sample multiview data. We are motivated by that the collected dataset contains redundant data that reflect nuisance variation of the same visual concept. Therefore, we first acquire a local data manifold distribution $Q(x|i(c))$, where $x$ denotes a data point, and regard it as an approximation of the underlying multiview distribution, i.e., $Q(x|i(c)) \approx P(v(c))$. The multiview data is then obtained by sampling data from the approximated multiview distribution,

$$v(c) \sim Q(x|i(c)).$$

### 3.2 Multiview Data from Local Data Manifold

In this section, we start from analyzing two simple methods, $k$NN and traversing GAN latent space, for modeling local data distribution. After that, we introduce our method that repurposes IC-GAN (Casanova et al. 2021) to achieve this goal. Finally, the merits of our method are discussed.

#### Sampling from $k$NN

Given a specific similarity metric, the local data manifold at a data point can be approximated with its $k$ nearest neighbors. Formally, given a pair of data $x_i$, $x_j$, the similarity is measured with distance induced by certain embedding function $f_\phi : \mathcal{X} \rightarrow \mathbb{R}^d$, i.e., $\|f_\phi(x_i) - f_\phi(x_j)\|_2$. This embedding function $h$ can be a convolutional neural network learned with SSL methods. Then sampling multiview data from the distribution of local data manifold can be written as sampling from its nearest neighbor set,

$$x_{t,i} \sim k\text{NN}(x_i),$$

where $k\text{NN}(x_i)$ denotes the set of $k$ nearest neighbors of $x_i$ in $\mathcal{D}$ based on the similarity metric and we use $\sim$ to denote a uniformly random sample from a set. However, since the nearest neighbor set is a finite set containing limited views, views created by this method is highly restricted. Hence, $k$NN may fail to provide sufficient data variation for multiview representation learning.

#### Traversing latent space

Supposing the global data distribution is available, one can achieve multiview data sampling by traversing the data distribution. In particular, the data distribution can be modeled with deep generative models such as GANs. GANs implicitly approximate the target data distribution by building up a model to favor a sampling process. This sampling process is realized by first sampling a latent variable from prior distribution, and then transforming the latent variable with into data with generator network. From the distribution perspective, generator network is like mapping a latent distribution, usually a noise distribution, to the target distribution. Traversing data distribution is therefore feasible by traversing the latent space.

Formally, given a trained generator $G : \mathcal{Z} \rightarrow \mathcal{X}$ mapping a random latent variable $z_i \in \mathcal{Z}$ to an image $x_i = G(z_i) \in \mathcal{X}$. Another view of $x_i$ can be sampled by first sampling a latent perturbation $\epsilon \sim p(\epsilon)$ and then forwarding the perturbed $z_i$ to generator

$$x_{t,i} = G(z_i + \epsilon).$$

Nonetheless, this method faces two challenges. First, this method can only generates multiview data for generated data instead of real data, which significantly limit its application. Second, such traversal is challenging to be controlled without external supervision. It is difficult to avoid trivial changes that can be hardly perceived and excessive
Finite views
Semantic Preserving
Infinite views
✘ Finite views
𝑮
✔ Semantic Preserving
✔ Infinite views ✘ Semantic Changed
(a) Sampling from kNN

(b) Traversing latent space

(c) Sampling from local data distribution

Figure 2: Illustration of different instantiation of local manifold augmentation.

alteration that intensively alter the semantic concept of the image. These issues makes traversing GAN latent space contribute little to improving self-supervised representation learning performance (Jahanian et al. 2022).

Sampling from local data distribution To allievate the above issues, we consider directly modeling the local data distribution. This modeling is also known as instance-conditioned generative model, which has been explored by recently proposed instance-conditioned GAN (IC-GAN) (Casanova et al. 2021) and shown great power in image synthesis. Instead of focusing on synthesis, we concern its ability to model local data distribution and repurpose IC-GAN for sampling multiview data.

Concretely, IC-GAN (Casanova et al. 2021) decomposes the real data distribution into a mixture of conditional distributions and task a conditional generator to fit each conditional distribution. Formally, the real data distribution is approximated as

\[ p_{\text{data}} = \int p(x|x_i)p(x_i)dh \approx \frac{1}{N}\sum_{i}p(x|x_i), \]

where \( p(x|x_i) \) represents a local data distribution at a data sample from dataset \( x_i \sim D \). Given this decomposition, a conditional generator \( G : Z \times \{I_i\}_{i=1}^{M} \rightarrow \mathcal{X} \) is constructed to take as input a random variable \( z \in Z \) and as condition a embedding vector \( f_\phi(x_i) \) and outputs an image

\[ x = G(z, f_\phi(x_i)), \quad z \sim p_z, \quad x_i \sim D, \]

where \( p_z \) denotes the prior distribution of \( z \), typically a normal distribution. \( G \) is trained against a discriminator to tell if generated images are realistic nearest neighbors of \( x_i \). In this way, \( G \) implicitly models the distribution the target local data distribution \( p(x|x_i) \) with its ability of sampling from local data distribution.

We wrap the generation process of IC-GAN, including the feature extraction of conditioning image, as a data augmentation operation, denoted as LMA(·). In particular, given an image \( x_i \), its augmented view \( x_{t,i} \) is created through

\[ x_{t,i} = \text{LMA}(x_i) = G(z, f_\phi(x_i)), \quad z \sim \mathcal{N}(0, 1). \]

Discussion As illustrated in Fig. 2, kNN can generate non-trivial views but only supports finite number of views. On the contrary, traversing data distribution can provide infinite number of views but is challenging to avoid trivial and excessive views. Traversing local data distribution can be understood as integrating these two methods and therefore is able to create infinite number of appropriate views.

3.3 Learning Discriminative Semantic Invariance

We integrate LMA into existing multiview representation learning approaches as in Algorithm 1. Note that LMA should be applied prior to other data augmentation \( \mathcal{T} \). The reason is that feature extractor used in IC-GAN is pretrained to be invariant to these data augmentation. LMA therefore would erase the effect of other data augmentation.

It is noteworthy that LMA is applied to each data point with a non-trivial probability \( \alpha < 1 \). Assuming LMA is always enabled, all data views would come from IC-GAN generation. However, GAN is notorious for mode collapse issue which lead a set of less diverse generated data than real dataset. The decreased diversity of training data would significantly hurt the performance of self-supervised representation learning, also evidenced by our experiment results (see Section 4.3 for analysis). Hence, we mitigate this issue by occasionally applying LMA, which would make the source of training data a mixture of real data and generated one and thereby prevent reducing the diversity of training data.

4 Experiments

4.1 Settings

Datasets Our method is evaluated on five datasets: CIFAR10, CIFAR100, STL10, ImageNet100, and ImageNet.
CIFAR10 and CIFAR100 (Krizhevsky 2009) are 32 × 32-resolution image datasets with 10 and 100 classes, respectively. Both CIFAR10 and CIFAR100 are split into 50,000 images for training and 10,000 images for validation. STL-10 (Coates, Ng, and Lee 2011) and ImageNet100 (Tian, Krishnan, and Isola 2020) are datasets derived from the ImageNet (Deng et al. 2009). STL-10 contains images at 96 × 96 resolution of 10 classes, which are further split into training set with 5,000 labeled images plus 100,000 unlabeled images and test set with 8,000 labeled samples. ImageNet100 contains images of 100 classes, including a train split of 126,689 images and a validation split of 5,000 images. ImageNet (Deng et al. 2009) is the most popular large-scale image dataset of 1000 classes, which consists of 1,281,167 training images and 50,000 validation images.

Training IC-GAN for LMA On CIFAR10, CIFAR100, and STL10, we first employ SimSiam (Chen and He 2021) without LMA to learn a feature extractor which is later used for feature extraction of conditioning images. Then we train an IC-GAN on train split for CIFAR10 and CIFAR100 with StyleGAN2 at 32 × 32 resolution as backbone, and on “train+unlabel” split of STL10 with StyleGAN2 at 128 × 128 resolution as backbone. For experiments on ImageNet100 and ImageNet, we utilize pre-trained IC-GAN that is publicly available. These pre-trained IC-GAN is repurposed for LMA. When applying LMA, by default, we use α = 0.3 for CIFAR10, CIFAR100, STL10, and ImageNet100 and α = 0.1 on ImageNet.

Integrating LMA into SSL We pre-train representation extractor on training set of each dataset with LMA-integrated SimSiam (Chen and He 2021) and MoCov2 (Chen et al. 2020b). For backbone feature extractor, we employ ResNet18 (He et al. 2016) on CIFAR10, CIFAR100, and STL10, where CIFAR variant of ResNet18 (Chen and He 2021) is specifically utilized on CIFAR-10 and CIFAR-100. ResNet50 is employed as backbone feature extractor on ImageNet100 and ImageNet. Other network details include projection (and prediction) heads follow the original practice of MoCov2 and SimSiam. As in MoCov2 (Chen et al. 2020b), the handcrafted augmentation includes random crop, color jittering, color discard, Gaussian blurring, and horizontal flip. Details are available in the appendix. SGD optimizer and cosine learning rate decay (Loshchilov and Hutter 2016) scheduler are used for training representation extractors. The actual learning rate is linearly scaled according to the ratio of batch size to 256, i.e., base lr × batch size / 256 (Goyal et al. 2017). Detailed hyperparameters are available in the appendix.

4.2 Main Results

Linear classification Following common practice in SSL (Chen et al. 2020a; Tian, Krishnan, and Isola 2020; He et al. 2020), the quality of learned representations is evaluated with the performance of a trained linear classifier atop the representations. Details are available in the appendix. Table 1 compares the results of SimSiam (Chen and He 2021) and MoCov2 (Chen et al. 2020b) on small- and medium-scale benchmarks under the settings of (1) only using handcrafted augmentation (HCA), (2) only using LMA, and (3) using both HCA and LMA (see Algorithm 1). It can be seen that supplement of LMA improves (setting 3 v.s. 1) the top-1 accuracy of SimSiam with 1.52%, 2.63%, 0.79%, and 4.62% and MoCov2 with 0.84%, 5.13%, 3.52%, and 11.00% on CIFAR10, CIFAR100, STL10, and ImageNet100, respectively. It is also noteworthy that by only using LMA the performance is not significantly decreased and sometimes surpass only using HCA: MoCov2 achieves 80.71% with only LMA against 79.20% on STL10, and 74.06% against 69.80% on ImageNet100.

Our method is further evaluated on the most popular large-scale dataset, ImageNet. In particular, we pretrain a ResNet50 with SimSiam for 100 epochs, Table 2 presents the results of SimSiam and MoCov2 with LMA as well as other augmentation-related methods for reference. It shows that LMA can consistently bring clear improvement, with 0.50% and 1.12% increase on top-1 accuracy for SimSiam and MoCov2. Our method also significantly outperforms augmentation by traversing BigBiGAN latent space (Jahanian et al. 2022), presenting a more promising way to realizing GAN-based augmentation.

We use IC-GAN pretrained on ImageNet at 128 × 128 resolution with BigGAN as backbone: https://dl.fbaipublicfiles.com/ic_gan/icgan_biggan_imagenet_res128.tar.gz.

| Methods | HCA | LMA | CIFAR10 | CIFAR100 | STL10 | IN100 |
|---------|-----|-----|---------|----------|-------|-------|
| SimSiam (Chen and He 2021) | ✓ | ✓ | 90.94 | 63.07 | 81.13 | 78.32 |
| MoCov2 (Chen et al. 2020b) | ✓ | ✓ | 91.18 | 59.76 | 79.20 | 69.80 |

Table 1: Linear classification performance on benchmarks at small and medium scales. “HCA” denotes the handcrafted augmentation. The top1 accuracy of the linear classifier atop pre-trained representations is reported. 1: IC-GAN pretrained on ImageNet-1K is employed for LMA on ImageNet100.

| Methods | Sources | # Epochs | Top1 Acc |
|---------|---------|----------|----------|
| SimCLR | Jahanian et al. (2022) | 20 | 43.90 |
| on BigBiGAN Syn. | Jahanian et al. (2022) | 20 | 35.69 |
| + BigBiGAN-Aug | Jahanian et al. (2022) | 20 | 42.58 |
| SimSiam | Peng et al. (2022) | 100 | 65.62 |
| + ContrastiveCrop | Peng et al. (2022) | 100 | 65.95 |
| MoCov2 | Ours | 100 | 62.48 |
| + LMA | Ours | 100 | 63.97 |
| SimSiam | Ours | 100 | 67.32 |
| + LMA | Ours | 100 | 67.82 |

Table 2: Linear classification performance on ImageNet. 1: Our reproduction results with α = 0.

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1We use IC-GAN pretrained on ImageNet at 128 × 128 resolution with BigGAN as backbone: https://dl.fbaipublicfiles.com/ic_gan/icgan_biggan_imagenet_res128.tar.gz.
**Table 3: Robustness evaluation.** Top-1 accuracy on ImageNet-like datasets with distribution shift.

| Methods       | IN-V2 (Top) | INv2 (Th0.7) | INv2 (Freq) | IN-R | IN Sketch | IN-A |
|---------------|-------------|--------------|-------------|------|-----------|------|
| MoCov2        | 63.88       | 57.78        | 49.21       | 23.73| 14.22     | 2.06 |
| + LMA         | **66.61**   | **59.40**    | **50.65**   | **25.22** | **15.49** | 1.74 |
| SimSiam       | 70.33       | 64.47        | 55.29       | 28.23| 18.08     | **2.64** |
| + LMA         | **70.58**   | **64.55**    | **55.55**   | **29.41** | **18.48** | 2.58 |

**Representation invariance** As LMA introduces additional nuisance variation such as object pose, viewpoint, lighting condition, etc., we further evaluate if the learned representations gain stronger invariance to such variation. To quantitatively measure the representation invariance, we follow Ericsson, Gouk, and Hospedales (2021) to extract representations and compute average pairwise cosine similarity for real-world images from datasets including Flickr1024 (Scharstein et al. 2014), COIL100 (Nene et al. 1996), ALOI (Geusebroek, Burghouts, and Smeulders 2005), ALOT (Burghouts and Geusebroek 2009), ExposureErrors (Afifi et al. 2021), RealBlur (Rim et al. 2020) that are collected with controlled variation such as stereo, pose/scale, viewpoint, illumination, color temperature, exposure, and blurring. Fig. 1b compares the representation invariance learned by MoCov2 with HCA, with LMA, and with HCA+LMA on ImageNet100. Detailed numbers are available in the appendix. Results show that LMA excels at invariance to pose, viewpoint, exposure and illumination but compromises in stereo, blur, and color temperature against HCA. Supplementing LMA to HCA is able to bring gain more invariance without losing original invariance much.

**Robustness to distribution shift** We further test the robustness of learned representation. In particular, we use the ImageNet-testbed (Taori et al. 2020) to test the feature extractor plus linear classifier head that are trained on ImageNet train split on several ImageNet-like datasets with distribution shift: ImageNet-V2 (IN-V2) (Recht et al. 2019) including topimages (Top), threshold0.7 (Th0.7), and matched frequency (Freq) splits, ImageNet-R (IN-R) (Hendrycks et al. 2021a), ImageNet Sketch (IN Sketch) (Wang et al. 2019), and ImageNet-A (IN-A) (Hendrycks et al. 2021b). Results in Table 3 show that with addition of LMA, the linear classifier can achieve higher performance on five out of six datasets with distribution shift, suggesting that the self-supervised representations strengthened by LMA gain stronger robustness.

**Visualization** We provide visualization of LMA effects in Fig. 3 and embedded representation distribution in Fig. 4. It can be observed that LMA is generally able to preserve the semantic contents and introducing non-negligible variation. With the help of LMA, the embedded representations are more discriminative for image classes.

**4.3 Analysis**

**Comparison to other transformation** In Table 4, we compare our method to kNN transformation and traversing GAN. In particular, kNN transformation approach uses as embedding network the same feature extractor as in pre-trained IC-GAN. It transforms a given image by replacing it with a random sample from its k nearest neighbors (see Equ. 3). Traversing GAN approach traverses the latent space (see Equ. 4) of a StyleGAN2 (Karras et al. 2020a) generator that is pretrained on CIFAR10 and CIFAR100. The perturbation is sampled from a Gaussian distribution with smaller std, i.e. \( \epsilon \sim N(0, 0.2) \).

According to the results, kNN transformation is not observed to consistently improve the performance of SimSiam and traversing GAN can bring slight improvement. In contrast, our method outperforms other related transformation and contribute significant improvement to SimSiam. As explained in the previous section, we attribute the success of LMA to its ability to generate infinite number of data of appropriate views. To further study the effect of the number of views, we weaken LMA to only favor finite-view generation. Concretely, we change the prior distribution of latent variables to a uniform distribution over a pre-sampled set. In this way, the LMA is restricted to create finite number of views. Table 5 shows that limiting the number of views significantly reduce the performance and this issue can be mitigated by increasing the number of views. These results verify our conjecture that the ability of creating infinite number of views is an criital ingredient that LMA contributes to the representation performance improvement.
Table 4: Comparison of multiple LMA variants on CIFAR10 and CIFAR100. The base SSL method is Simsiam. For kNN transformation, we use \( k = 20 \) for CIFAR10 and \( k = 5 \) for CIFAR100, the same as ones used for training IC-GAN. All the transformations are applied with probability 0.3. * denotes the default setting.

| LMA variants | CIFAR10       | CIFAR100      |
|--------------|---------------|---------------|
|              | Top1 Acc | Top5 Acc | Top1 Acc | Top5 Acc |
| w/o LMA      | 90.94    | 99.60    | 63.07    | 87.56    |
| kNN          | 89.56    | 99.52    | 63.14    | 87.84    |
| StyleGAN2    | 91.67    | **98.80** | 63.81    | 88.75    |
| * IC-GAN     | **92.46** | 99.73    | **65.70** | **89.92** |

Table 5: Ablation w.r.t. number of views on CIFAR10. * indicates the default setting. “Inf” denotes infinite number.

| # LMA views | w/o LMA | w/LMA |
|-------------|---------|-------|
|             | 90.94   | 90.83 | 91.13 | 91.42 | 91.06 | **92.46** |

Probability of applying LMA As analyzed in Section 3.3, the introduction of LMA makes two changes to the training data: (1) the source of training images, i.e. real data or generated data, and (2) multiview training data, i.e. the view variation of the data. Since LMA relies on generative model to create multiview data, it is impossible to administer the second without the first ingredient. To solely impose the first ingredient, we consider a reference method, “SimSiam-mix”, where in a mini-batch of training data, training images are possible to be sampled from both real dataset and generator. Similarly to Algorithm 1, a hyperparameter \( \alpha \) controls the possibility of sampling from generator. In this way, for both “SimSiam-mix” and “SimSiam+LMA”, the source of training data would be (1) real data when \( \alpha = 0 \), (2) a mixture of real and generated data when \( 0 < \alpha < 1 \), and (3) generated data when \( \alpha = 1 \). Beyond that, “SimSiam+LMA” enjoys richer multiview data from LMA compared to “SimSiam-mix”.

Fig. 5 plots the performance of these two methods with respect to different \( \alpha \). It can be observed that the optimal \( \alpha \) is around 0.3 for both CIFAR10 and CIFAR100. Note that the performance when \( \alpha = 1 \) is lower than performance when \( \alpha = 0 \) for these two methods, suggesting that the pre-trained IC-GAN is unable to generate data of matching quality to real data. Despite so, the performance of training on a mixture of data is higher than that on real data (see the performance of SimSiam-mix when \( \alpha = 0.3 \) versus \( \alpha = 0 \)), suggesting that generated data does have some complementary effect to real data. Finally, “SimSiam+LMA” clearly outperforms “SimSiam-mix”, indicating that extra data variation from LMA do contribute to the improvement of representation learning.

The impact of pre-trained IC-GAN Since LMA heavily relies on the pre-trained IC-GAN, we study how is the performance of our method related to the pre-trained IC-GAN. We ablate the \( k \) in kNN when pre-training IC-GAN and show the results in Table 6. Generally, if \( k \) is increased, the IC-GAN can gain higher quality of generated data, suggested by lower FID and higher performance of “SimSiam-mix”. It can be seen that with improved quality of pre-trained IC-GAN, the performance of our method can be further improved.

Furthermore, we use various IC-GANs that are not well-trained for LMA to investigate the impact of the quality of IC-GAN on the performance our method. In particular, we select the checkpoints of different FID that are saved during training process and run SimSiam with LMA (\( \alpha = 0.3 \)) on CIFAR10. Fig. 6 plots the linear classification top1 accuracy versus FID. It shows that LMA can provide more improvement given a IC-GAN of higher quality.

| # LMA views | w/o LMA | w/LMA |
|-------------|---------|-------|
|             | 90.94   | 90.83 | 91.13 | 91.42 | 91.06 | **92.46** |

Table 6: Ablation w.r.t. kNN when pretraining IC-GAN. * denotes default setting.

5 Conclusions

In this paper, we construct local manifold augmentation (LMA) motivated by utilizing the rich data variation underlying the dataset. This is achieved by repurposing a pre-trained IC-GAN for data augmentation. LMA is able to provide richer data variation that includes complicated geometrical and appearance change and able to improve SSL performance, representation invariance and representation robustness. Dedicated steeration to purify the useful data variation for representation learning is important to fine-grained recognition tasks and complicated and variable real-world scenarios, which is a open challenge left as future work.
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A Implementation Details

A.1 Training IC-GAN

Training IC-GAN requires a pre-trained feature extractor to embed images into feature vectors for nearest neighbor search and condition input. On CIFAR10, CIFAR100, and STL10, we employ SimSiam (Chen and He 2021) with only handcrafted augmentation to learn such feature extractors. Table 7 summarizes the top-1 and top-5 accuracies of feature extractors as well as other hyperparameters for training IC-GANs. The generator with the lowest Fréchet Inception distance (FID) during training process is chosen and repositioned for LMA.

A.2 Handcrafted data Augmentation

The construction of handcrafted augmentation follows the prevalent practice (Chen et al. 2020b), which is composed in the following sequence.
| Dataset   | Feature extractor | Split | Res. | Backbone | Cfg.  | Duration (kimg) | Top1 Acc | Top5 Acc |
|-----------|-------------------|-------|------|----------|-------|-----------------|----------|----------|
| CIFAR10   |                   | train | 32   | StyleGAN2 | cifar | 100,000         | 90.94    |          |
| CIFAR100  |                   | train | 32   | StyleGAN2 | cifar | 100,000         | 63.07    | 87.56    |
| STL10     |                   | train+unlabel | 128 | StyleGAN2 | auto  | 25,000         | 81.13    | 98.88    |

Table 7: Hyperparameters for training ICGAN on CIFAR10, CIFAR100, and STL10.

| Method   | Dataset | Input scale | Backbone | Weight decay | Base lr | PASCAL VOC |
|----------|---------|-------------|----------|--------------|---------|------------|
|          |         |             |          |              |         | AP50       | AP        | AP75      |
| MoCov2   | IN      | 224         | R50      | 0.001        | 0.05    | 79.42      | 53.64     | 58.92     |
|          | IN100   | 96          | R50      | 0.001        | 0.05    |            |           |           |
| MoCov2   | CIFAR10 | 32          | R18-C    | 0.005        | 0.03    | 79.95      | 53.78     | 59.19     |
|          | CIFAR100| 32         | R18-C    | 0.005        | 0.03    |            |           |           |
| MoCov2   | STL10   | 128         | R18      | 0.005        | 0.05    |            |           |           |

Table 9: Transfer learning evaluation. Backbone encoder is pre-trained on ImageNet100, and IC-GAN pre-trained on ImageNet-1K is employed for LMA.

| Methods | 1% label | 10% label |
|---------|----------|-----------|
|         | Top-1 Acc | Top-5 Acc | Top-1 Acc | Top-5 Acc |
| MoCov2  | 33.80    | 53.90     | 72.60     | 92.40     |
| + LMA   | 46.50    | 66.80     | 78.10     | 94.80     |

Table 10: Semi-supervised evaluation on ImageNet100. Backbone encoder is pre-trained on ImageNet100.

B Visualization

Please see Fig. 7 and Fig. 8 for more visualization of LMA effects.

C More Evaluation Results

Besides this linear classification evaluation, we also conduct semi-supervised learning following (Chen and He 2021) to evaluate the representation quality and transfer learning following (He et al. 2020) to evaluate the transferability of the learned representations. Additional details about representation invariance evaluation are also appended.

C.1 Transfer learning

Following (He et al. 2020), the transferability of learned representations is evaluated with object detection task on PASCAL VOC. In particular, we pre-train ResNet50 on ImageNet100, initialize the backbone of R50-C4 in Faster R-CNN with the pre-trained one, train Faster R-CNN on the VOC trainval2007+2012 split, and report its performance on the VOC test2007 split. All network layers are trainable and finetuned during training. Tab. 9 presents the results, showing that LMA provides marginal improvements on downstream tasks.

C.2 Semi-supervised learning

Similarly to (Chen et al. 2020a), after pre-training representations on ImageNet100, we leverage a small subset of the available labels in the ImageNet100 train split to finetune a classification network. Table 10 reports the top-1 and top-5 accuracy on the ImageNet100 val split. The results show that large improvement can be obtained with the help of LMA, 12.70%/12.90% top-1/top-5 accuracy improvement when 1% labels are used and 7.50%/2.40% top-1/top-5 accuracy improvement when 10% labels are used.

C.3 Representation invariance details

We follow Ericsson, Gouk, and Hospedales (2021) to evaluate the invariance of representations with respect to various real-world transformation. Table 11 presents the detailed
Table 11: Real-world transformation invariance is measured with cosine similarity (↑) and Mahalanobis distance (↓) following Ericsson, Gouk, and Hospedales (2021). The feature extractor is pre-trained on ImageNet100 using MoCov2.

| Variation | Dataset       | Stereo | Pose/Scale | Viewpoint | Illumination | Temperature | Exposure | Blur |
|-----------|---------------|--------|------------|-----------|--------------|-------------|----------|------|
|           | Flickr1024    | 0.94   | 0.75       | 0.79      | 0.68         | 0.84        | 0.70     | 0.98 | 0.95 | 0.86 | 0.92 |
|           | COIL100       | 0.92   | 0.81       | 0.80      | 0.72         | 0.86        | 0.81     | 0.97 | 0.94 | 0.88 | 0.84 |
|           | ALOI          | 0.93   | 0.79       | 0.81      | 0.71         | 0.86        | 0.76     | 0.98 | 0.95 | 0.90 | 0.89 |
|           | ALOT          |        |            |           |              |             |          |      |      |      |      |
| Cosine similarity (↑) |
| MoCov2 w/ HCA | 17.24 | 28.10  | 19.87      | 46.82     | 18.86        | 48.80       | 4.72     | 24.38| 20.09| 15.31|
| MoCov2 w/ LMA | 26.41 | 28.67  | 23.31      | 49.93     | 20.36        | 44.28       | 9.15     | 30.18| 23.87| 31.39|
| MoCov2 w/ HCA + LMA | 18.34 | 25.97  | 18.14      | 41.99     | 16.51        | 40.93       | 6.12     | 22.85| 16.29| 19.88|
| Mahalanobis distance (↓) |
| MoCov2 w/ HCA |        |        |            |           |              |             |          |      |      |      |      |
| MoCov2 w/ LMA |        |        |            |           |              |             |          |      |      |      |      |
| MoCov2 w/ HCA + LMA |        |        |            |           |              |             |          |      |      |      |      |

numbers. We use the evaluation results of cosine similarity to plot the radar chart in the Fig.1b in the main text.
Figure 7: **Visualization** of LMA on CIFAR10 and CIFAR100.
Figure 8: **Visualization** of LMA on STL10 and ImageNet.