Abstract

We present Contrastive Neighborhood Alignment (CNA), a manifold learning approach to maintain the topology of learned features whereby data points that are mapped to nearby representations by the source (teacher) model are also mapped to neighbors by the target (student) model. The target model aims to mimic the local structure of the source’s representation space using a contrastive loss. CNA is an unsupervised learning algorithm that does not require ground-truth labels for the individual samples. CNA is illustrated in three scenarios: manifold learning, where the model maintains the local topology of the original data in a dimension-reduced space; model distillation, where a small student model is trained to mimic a larger teacher; and legacy model update, where an older model is replaced by a more powerful one. Experiments show that CNA is able to capture the manifold in a high-dimensional space and improves performance compared to the competing methods in their domains.

1. Introduction

In this paper, we present a new algorithm, Contrastive Neighborhood Alignment (CNA), that preserves the local topology of learned features between source and target models by mapping neighbors in one space (source) to neighbors also in the target (student) space. CNA overcomes the optimization challenge in the formulation of traditional manifold learning methods for large-scale computing by designing a contrastive loss that can be trained effectively to preserve the local topology of the feature space. The model learned through CNA is inductive and hence can generalize to novel data. CNA is an unsupervised approach and requires no ground-truth labels. Fig. 1 illustrates the local topology preservation by CNA, that the neighbors \((x_5, x_7, x_8)\) of a sample \(x_1\) (Fig. 1 left) in the source space is well-preserved in the target model space trained by CNA(Fig. 1 right).

CNA does not impose constraints on source models and it can be adopted to performing student-teacher learning for tasks such as knowledge distillation (KD) [16] and reducing model regression in model updating [51], beyond the standard manifold learning tasks [9, 34, 42]. Conventional knowledge distillation and student-teacher (S-T) learning [1, 7, 16, 47] approaches primarily follow the design principle of matching features or classification distributions between the teacher and student models [47]. Despite the effectiveness of the feature/distribution matching criterion, S-T learning methods are not without limitations. Typically, student-teacher training tries to force the student to mimic the input-output behavior of the teacher, but the regularization term (model bias) often results in a direct conflict with the cross-entropy (CE) loss, i.e., KL-divergence/logit-matching vs. softmax. This has two problems. First, the criterion trades off error rate minimization. Second, the criterion is too rigid in that it mimics the teacher’s predictions without the awareness of the data manifold. In contrast, CNA tackles the student-teacher learning problem by modeling the knowledge in the models using the local structures in their feature space, which is distinct from the existing methods in model distillation [16].

CNA is a new inductive principle: instead of mimicking the input-output behavior, it transfers the local neighbor-
hood structure. Neighbors remain neighbors, when transferring from the source to the target, regardless of the label. This has two distinct advantages: first, it does not require ground truth labels. Second, it allows more flexibility to deviate from the inference of the source model when it is mistaken. In CNA, we impose that samples are neighbors in the source (teacher) representation space remain neighbors in the target (student) representation space. This alignment of local neighborhoods is achieved by adding to the cross-entropy loss a contrastive term that is in the same form (softmax function) as the cross-entropy term, making the optimization well conditioned; as both the cross-entropy and the contrastive loss are in similar unit spaces (normalized softmax function), balancing the two terms becomes relatively easy. The contributions of our work are listed below:

- We propose a new method for manifold learning that maintains the local neighborhood in inductive models.
- We introduce an instance-level contrastive loss for preserving the neighborhood structures that is different from how contrastive loss is motivated and implemented previously [15, 30, 49].
- We propose to use a new loss function in Student-Teacher training, which is distinct from the existing methods in this field.

The effectiveness of CNA is demonstrated on three tasks, 1) dimensionality reduction for manifold learning [45], 2) model distillation [16], and 3) model update regression minimization [51]. CNA is capable of capturing the manifold from the source space and can be applied to various downstream tasks in knowledge distillation.

2. Related work

**Manifold/metric learning:** Preserving local neighborhood structure is a popular direction in machine learning that has been explored in both metric learning [8, 17, 26, 52] and manifold learning [34]. Standard manifold learning approaches perform dimensionality reduction by mapping the feature representation from the original space to the new one [45]. They attempt to maintain the local structure through the reconstruction by the convex combination of same neighbors [9, 34], by retaining the neighborhood distances while unfolding the manifold [48], or by preserving pairwise geodesic distances between all data points [42]. These manifold learning methods learn the manifold transductively, which limits their deployments in modern deep networks. In contrast, Our CNA adopts an instance-level contrastive loss that attempts to preserve the manifold structure of feature space in an inductive model, which is significantly different from these works. Additionally, CNA can be combined with classification loss (e.g. a cross-entropy loss) to create classifiers when training deep models.

**Contrastive learning and self-supervised learning:** Contrastive learning [12] is used for either supervised [20, 37, 41] or unsupervised [6, 14, 49] representation learning. It has recently become popular in self-supervised learning through the instance discrimination pretext task [49]. Contrastive representation distillation (CRD) [43] extends the idea of contrastive learning to the teacher-student training case. Though not directly minimizing a certain distance function, CRD still needs to calculate the distance between student’s feature vectors and that of the teacher. CNA uses the contrastive loss form in teacher student training but does not measure the “cross model distance”. It only concerns the local structures within the models’ feature spaces. The supervised contrastive learning method [20] is also different from CNA since we focus on preserving the local neighborhoods between models as opposed to using class labels to learn visual representation.

**Model distillation:** There has been a significant amount of work to study how knowledge can be shared between multiple models. Model distillation [16, 47] transfers knowledge from a larger, more powerful teacher model to a smaller student model by matching their output/representation. CNA does not rely on matching outputs [16, 51] or reusing the old models’ parameters [38]. Instead, knowledge is shared between models through the information encoded in the neighborhood structure of a model’s feature space.

**Regression minimization for model upgrading:** The presence of new errors that were not manifest when using the old model (negative flips) can cause a perceived reduction of performance by users, referred to in the industry as “regression.” Although progress in the design of the architecture of backbone models [15, 18, 19, 39, 40, 46, 50], new optimization and regularization schemes [4, 10, 24], and the availability of new datasets [3, 22, 25, 28, 33, 35] have driven a fast-paced reduction of the average error rate (AER) of image classifiers, regression is still a major obstacle to the deployment of improved models. Even a modest number of negative flips can nullify the benefit of a large decrease in AER. Overall, the problem of reducing the negative flip rate (NFR), along with the average error rate (AER), has been referred to as Positive-Congruent Training, or PC-Training [51]. Minimizing model regression during model upgrading is an emerging problem that is of great practical importance [51]. In [51], NFR is proposed as the metric to measure regression in classification model updates and an approach based on focal distillation, a variant of model distillation [16], is proposed to reduce regression. Our work addresses the same problem through contrastive neighbor alignment instead of relying on model distillation.

3. Contrastive Neighborhood Alignment

Given a possibly pretrained source model $S$ and a dataset $\mathcal{D} = \{x_i\}$, it is a common task to transfer information
Figure 2. Qualitative results of manifold learning on synthetic datasets. Rows (top to bottom): S-curve, Swiss Roll, Sphere. Columns (left to right): original 3D data points, transductive methods (Isomap [42], LLE [34], Hessian LLE [9]), inductive methods (MVU [48], CNA).

from the source model $S$ to a newly trained target model $T$. Let $f_S(\cdot)$ and $f_T(\cdot)$ denote the feature representation of the source and target model, respectively. The two models could have different architectures or different feature dimensions. For example, in manifold learning [45], the high-dimensional source feature space is cast to a target space in which the low-dim manifold is unveiled. In model distillation, knowledge is shared between models by minimizing the sample-wise pseudo-distance between the two models’ classification posterior probabilities. In this work, we propose CNA, a contrastive loss that transfers information between models by preserving the local structures of the source model feature space in that of the target. An illustration of this idea is shown in Fig. 1. Below, we detail the derivation of the CNA loss function and its applications in model distillation/update tasks.

### 3.1. Preserving Local Structure

The idea of replicating the local structure in a new feature space has been explored in the manifold learning literature [45]. For example, Isomap [42] preserves pairwise geodesic (or curvilinear) distances between samples. The geodesic distances are computed by constructing a neighborhood graph in which every sample $x_i$ is connected with its top-$K$ nearest neighbors. Locally linear embedding (LLE) [34] studied the local structure in the nonlinear feature space. It has shown that by embedding high-dimensional feature vectors in their local neighborhoods, we can obtain effective low-dimensional embedding of the data points. LLE assumes each data point and its neighbors lie on a locally linear patch in the source space, and characterizes the local structure by a linear reconstruction using the neighbors:

$$\epsilon(W) = \sum_i \|f_S(x_i) - \sum_j W_{i,j}f_S(x_j)\|_2^2$$ (1)

where $f_S(x_i)$ is the feature representation of $x_i$ in the source space, $\epsilon$ is the reconstruction error and $W$ is the coefficient matrix. $W_{i,j}$ is enforced to 0 if $x_j$ is not one of the top-$K$ neighbors of $x_i$ and $\sum_j W_{i,j} = 1$. The solution $W^* = \arg \min \epsilon(W)$ is then used to obtain the target representation by minimizing the reconstruction error in the target space. Maximum Variance Unfolding (MVU) [48] is another work that focuses on retaining pairwise distances in a neighborhood graph. It maximizes the sum of distances between all data points in the target space:

$$\max \sum_{i,j} d(f_T(x_i), f_T(x_j)),$$ (2)

under the constraint that the distances between the neighbors are preserved: $d(f_T^{(i)}, f_T^{(j)}) = d(f_S^{(i)}, f_S^{(j)})$ if $x_j$ is one of the top-$K$ neighbors of $x_i$. Here $d(\cdot, \cdot)$ is the $\ell_2$ distance.

However, these manifold learning methods are difficult to be employed in modern deep learning frameworks. They often need to store a local structure graph for the entire...
Traditional manifold learning is designed to encourage the target model to maintain the topology. And the contrastive neighborhood alignment loss $\ell_{CNA}(x_i) = -\log \frac{\exp[\ell_T(x_i) \cdot \ell_T(N(x_i))/\tau]}{\sum_{j \neq i} \exp(\ell_T(x_i) \cdot \ell_T(x_j)/\tau)}$, where $\tau$ is the temperature, and $\ell_T(\cdot)$ the target feature extractor and its output is assumed normalized. Instead of directly minimizing the distance between neighbors, in Eq. (5), the neighbor pairs defined by the source model are pulled together but the non-neighbor pairs will be pushed away during the target model training. In this way, the local structure is preserved, and the knowledge encoded in the structure is transferred to the new model.

The contrastive loss has the same softmax form as the cross-entropy loss, and this helps when both losses need to be jointly optimized. More importantly, there is no longer a direct requirement to match the source and target outputs. This relaxation enables the CNA to be applicable even when the target model is trained with different loss functions or has different feature dimensions.

While the CNA loss of Eq. (5) only considers the nearest neighbor, it can be easily generalized to top-$K$ nearest neighbors,

$$\ell_{CNA}^K(x_i) = \frac{1}{K} \sum_{\tilde{x} \in N^K(x_i)} -\log \frac{\exp[\ell_T(x_i) \cdot \ell_T(\tilde{x})/\tau]}{\sum_{j \neq i} \exp(\ell_T(x_i) \cdot \ell_T(x_j)/\tau)},$$

where $N^K(x_i)$ is the top-$K$ nearest neighbors of sample $x_i$. This formulation simply averages the CNA losses of multiple neighbors.

Transductive vs. Inductive: Traditional manifold learning methods are transductive as they infer the target representation for each data point directly by optimizing the objective. It is advantageous in capturing the manifold of training data since the projection is not limited by any function. But they are hard to generalize to novel data as it requires modification of the original graph. Our CNA is fundamentally different as we learn an inductive target model by making the new model mimic the local structure of the source representation space. In experiments, we show that CNA can also be used to learn an inductive model, and it is non-trivial to adapt the transductive method into an inductive model.

3.3. Model Distillation/Update

By distilling the knowledge of the source (teacher) model to the target (student) model, the target model can achieve higher accuracy [16] or maintain consistency when the model is updated [51]. There are various definitions of knowledge which leads to different approaches to transfer it. The objective can be to minimize the sample-wise feature distance between two models with respect to a feature distance function, usually $\ell_2$-distance [36]. Recent works also proposed to use the contrastive loss [20] instead of minimizing absolute distance. Our CNA can also be used in these tasks, by carrying the knowledge of the teacher model to the student model by preserving the local structure of the feature space.

Let us consider a classification problem. Let $y_i \in \{1, 2, \ldots, C\}$ denote the class label for each data sample $x_i$. $h(\cdot, \cdot)$ is the classifier following the feature extractor $f(\cdot)$ to predict the class label, $\hat{y} = \arg \max_y h(f(x), y)$. In order to learn the full target classification model $\{f_T, h_T\}$ capable of preserving the local topology of the teacher model, the final objective is defined as the weighted sum of the standard
cross-entropy loss and the CNA loss:

\[ L_{CNA} = \frac{1}{M} \sum_{i}^{M} [\ell_{CE}(x_i, y_i) + \lambda \ell_{CNA}(x_i)], \quad (7) \]

where \( \lambda \) is the trade-off coefficient, and \( \ell_{CE} \) is the cross-entropy loss,

\[ \ell_{CE}(x_i, y_i) = -\log \frac{\exp(h_T(f(x_i), y_i))}{\sum_c \exp(h_T(f(x_i), y_c))}, \quad (8) \]

where \( y_c = 1, 2, \ldots, C \) refers to each class in the datasets. Note that the prediction of the source model \( h_S(\cdot, \cdot) \) is not present in the loss function Eq. (7), unlike the distillation term in knowledge distillation methods [16]. Thus, the two terms in Eq. (7) stay congruous even if the source model makes mistakes. As stated before, another major advantage of our proposed CNA loss is the formulation consistency between the two terms, and balancing the two terms in the loss function is relatively easy.

4. Experiments

We first evaluate the performance of the proposed CNA method on the unsupervised dimensionality reduction task and compare to other manifold learning techniques. CNA is then evaluated on two real-world application tasks: model distillation (from a large to small model) and model update (from a small to a large model).

4.1. Manifold Learning/Dimensionality Reduction

In a dimensionality reduction task, the goal is to learn a low-dimensional embedding that captures the manifold in the high-dim data space and favors downstream classifications. The source model \( f_S(\cdot) \) reduces to an identity function and the target model \( f_T(\cdot) \) is a projector that maps data to a lower dimensional space. We perform the experiments on synthetic datasets and natural datasets. On synthetic datasets, we show qualitative results to demonstrate that CNA is capable of discovering the manifold in a low-dimensional space. On natural datasets, we report quantitative results to measure the quality of the learned embeddings. In this task, CNA is employed in an unsupervised fashion where the cross-entropy loss in Eq. (7) is absent.

**Baselines:** We compare to three transductive manifold learning methods: Isomap [42], LLE [34] and Hessian LLE [9]. We use CNA to learn an inductive function through neural networks on both synthetic and real-world data. We also propose an inductive baseline trained by a modified MVU [48] objective. Specifically, this baseline uses the same inductive network as CNA and is trained by:

\[ \ell_{MVU} = \frac{1}{M} \sum_{i}^{M} \left\{ \frac{1}{K} \sum_{j: x_j \in N^K(x_i)} d(f_S(x_i), f_S(x_j)) \right. \\
- d(f_T(x_i), f_T(x_j))^2 - \frac{1}{\gamma} \sum_{j: x_j \in N^K(x_i)} d(f_T(x_i), f_T(x_j)) \left\} \right. \]

(9)

where \( \gamma \) is a balance weight. Basically, this loss function will push non-neighbor data points far away while keeping the distance between neighbors in the target space. During the experiments, we found a small \( \gamma \) is necessary (1e-6 e.g.) to avoid trivial solutions where every sample is isolated.

**Implementations:** For Isomap, LLE and Hessian LLE, the only free parameter is the number of neighbors \( K \). We set it to 10 on synthetic data and sweep over \([5, 10, 50, 100, 200]\) on real-world datasets. For MVU and CNA, we use a 3-layer multi-layer perceptron (MLP) with Tanh activation function as the inductive projection model. All networks are trained by Adam optimizer [21] with batch size 256. We fine-tuned the learning rate, number of neighbors \( K \), temperature \( \tau \) and \( \gamma \) in Eq. (9) on a held-out validation set.

4.1.1 Synthetic Data

We performed experiments on three synthetic datasets: S-Curve, Swiss Roll, and Sphere. Data points lie on a two-dimensional manifold in the original 3D space. The plots of the datasets are shown in the left column of Fig. 2. All datasets contain 2000 samples. The learning is considered good if the manifold is unfolded and the local structure is retained in the projected 2D space. In the experiments, the MVU and CNA networks have an intermediate layer with 5 nodes and hence 60 total parameters. All networks are trained for 2000 epochs. We visualize the learned manifolds for all the methods in Fig. 2.
The results show that the proposed CNA is capable of unfolding the manifold on all three synthetic datasets. The data points with similar colors stay neighbors in the projected space. Hence the local topology is well maintained. Transductive manifold learning methods can also unfold the manifold. However, on Swiss Roll dataset, the inductive MVU method fails to retrain the manifold even though we extensively fine-tuned the parameters. This indicates the non-triviality of achieving manifold learning using inductive networks. Notice that although the reconstructed manifolds of CNA for Swill Roll have a non-linear warping, they are not considered poor as the local structure of the two manifolds is identical to that of Isomap and Hessian LLE. Moreover, compared to transductive methods, CNA can learn the manifold using an inductive function with a handful parameters.

4.1.2 Real-world Data

We conducted experiments on two real-world datasets: MNIST [27] and CIFAR10 [23]. On MNIST we use the original data (784-dim) as source space, and on CIFAR10 we use the perceptual features (512-dim) of a pretrained ResNet18 model as the source data. For computational efficiency, we randomly select 4000 samples as training data and 1000 samples as test data. The intermediate layer of the MVU and CNA networks has 512 nodes. The networks are trained by 1000 epochs. The data is projected to a 40-dim space except for Hessian LLE because the number of neighbors required is proportional to the square of dimension [48]. The baseline transductive methods are more competitive, not less, as we found dim=40 works the best for most transductive methods.

Metrics: We evaluated two metrics: local error and 5-NN competitive, not less, as we found dim=40 works the best for CIFAR10. The baseline transductive methods are more competitive, not less, as we found dim=40 works the best for most transductive methods.

Table 2. The model distillation results (top-1 accuracy in %) on CIFAR100. * denoted results run by us. The other results of the competitors are from [43].

| Teacher (Source) | ResNet56 | ResNet110 | ResNet110 | ResNet32x4 | ResNet32x4 | ResNet32x4 | ResNet32x4 | ShuffleNetV1 | ShuffleNetV2 |
|------------------|---------|-----------|-----------|------------|------------|------------|------------|-------------|-------------|
| ResNet20 | 72.90 | 74.25 | 74.25 | 79.67 | 79.67 | 79.67 | 79.67 | 71.76 |
| ResNet20 | 69.96 | 69.96 | 71.26 | 72.68 | 70.98 | 71.76 |
| KD* [16] | 71.82 | 71.33 | 73.81 | 73.55 | 75.05 | 75.44 |
| SP1 [-] | 69.67 | 70.04 | 72.69 | 72.94 | 73.48 | 74.36 |
| CC [32] | 69.63 | 69.48 | 71.48 | 72.97 | 71.14 | 71.29 |
| VID [2] | 70.38 | 70.16 | 72.61 | 73.09 | 73.38 | 73.40 |
| RKD [31] | 69.61 | 69.25 | 71.82 | 71.90 | 72.28 | 73.21 |
| LFA* | 71.85 | 71.28 | 73.79 | 72.41 | 75.07 | 75.43 |
| CNA (ours) | 71.96 | 71.30 | 73.63 | 74.66 | 75.28 | 75.44 |

Table 3. The model distillation results (top-1/top-5 accuracy in %) on ImageNet.

| ResNet34 | ResNet18 KD [16] CRD [43] LFA | CNA (ours) |
|---------|--------------------------------|------------|
| top-1   | 73.31 | 69.76 | 71.33 | 71.17 | 71.41 | 71.38 |
| top-5   | 91.42 | 89.08 | 90.35 | 90.13 | 90.36 | 90.19 |

| ResNet50 | ResNet18 KD [16] CRD [43] LFA | CNA |
|----------|--------------------------------|-----|
| top-1    | 76.13 | 69.76 | 71.25 | - | 70.80 | 71.43 |
| top-5    | 93.55 | 89.08 | 90.53 | - | 90.13 | 90.27 |

4.2 Real-World Applications

We evaluated the proposed CNA method on two real-world tasks: model distillation and model update. In both tasks, information from one model is expected to transfer to another model, and our CNA method can be applied by considering the teacher (old) model as source and the student (new) model as target in model distillation (update). ImageNet [35] and CIFAR100 [23] are the two major datasets used for evaluation. The used network architectures are the standard ResNet variants [15] on ImageNet, and ResNet [15] and ShuffleNet [29, 53] on CIFAR100 following [43].

Training Details: For CIFAR100 (ImageNet), the base initial learning rate was 0.2 (0.1) for batch size of 256, linear scaling [11] was used for other batch sizes, and cosine learning rate decay schedule was adopted. Weight decay was set as 0.0001 for all ImageNet experiments, but it is sensitive and we searched the best one from {0.0001, 0.0002, 0.0005} for CIFAR100. SGD was used for optimization in all experiments. For CNA, we set \( \lambda = 1.0 \) in Eq. (7) and temperature \( \tau = 0.01 \) in Eq. (5) for all experiments. Each experiment of CIFAR100 (ImageNet) is conducted on 4 (8) V100 GPUs for about 1 (15) hour(s). The results were averaged on 5 runs for all CIFAR100 experiments. More details will be introduced in the following section.
4.2.1 Baselines

Knowledge Distillation was proposed in [16] to distill the knowledge from a pre-trained source (teacher) model to a newly trained target (student) model. It forces the target output probabilities to mimic those of the source, by minimizing a KL divergence loss between them,

$$\ell_{KD}(h_T(x_i), h_S(x_i)) = \tau^2 KL(h_T(x_i)/\tau, h_S(x_i)/\tau),$$

(10)

where $h(\cdot)$ is the classifier prediction, $KL$ is KL divergence and $\tau$ is the temperature.

Local Feature Alignment: To address the issue that LLE [34] lacks the ability of generalizing to points unknown to training data, [13] proposed to learn a non-linear mapping to preserve the local neighborhood by contrastive learning. This idea can also be applied here to align the local feature representations, called local feature alignment (LFA). Given the feature representations of the source model $f_S(x_i)$ and the target model $f_T(x_j)$, the idea is to pull them together if $x_i$ and $x_j$ are the same sample, otherwise repel them. The loss is defined as:

$$\ell_{FA}(x_i, x_j) = \mathbb{1}[i = j] \frac{1}{2} ||f_T(x_j) - f_S(x_i)||_2^2$$

$$+ \mathbb{1}[i \neq j] \frac{1}{2} [\max(0, \xi - ||f_T(x_j) - f_S(x_i)||_2)]^2 \quad (11)$$

where $\mathbb{1}[\cdot]$ is an indicator function and $\xi$ is a margin hyper-parameter in the hinge loss term. Similar to CNA loss of Eq. (5), local structure can be aligned by LFA, but the difference is LFA directly optimizes on the $\ell_2$ feature distance.

Similar to Eq. (7), the KD loss of Eq. (10) and FA loss of Eq. (11) is jointly optimized with a cross-entropy loss with trade-off coefficient $\lambda$ in the model distillation task.

4.2.2 Model distillation

We compare CNA to the KD and LFA baselines as introduced in Sec. 4.2.1, and the recent contrastive representa-

| batch size | 32 | 64 | 128 | 256 | 512 | 1024 |
|------------|----|----|-----|-----|-----|------|
| CIFAR100   | 71.51 | 71.36 | 71.87 | 71.79 | 71.96 | - |
| ImageNet   | -  | 70.75 | 70.87 | 71.08 | 71.38 | - |

Table 4. Ablation studies on batch size.

Figure 3. Results of model upgrade on CIFAR100 and ImageNet. X-axis: negative flips rate (NFR) in %, lower is better. Y-axis: new model accuracy in % higher is better. The idea model is expected to be located in the top-left corner.

Figure 3. Results of model upgrade on CIFAR100 and ImageNet. X-axis: negative flips rate (NFR) in %, lower is better. Y-axis: new model accuracy in % higher is better. The idea model is expected to be located in the top-left corner.

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|------------|----|----|-----|-----|-----|------|
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We compare CNA to the KD and LFA baselines as introduced in Sec. 4.2.1, and the recent contrastive representa-
fraction of negative flips:

\[
\text{NFR} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[\hat{y}_n^{(i)} \neq y_i \text{ and } \hat{y}_o^{(i)} = y_i]
\]

where \(\hat{y}_n^{(i)}\) and \(\hat{y}_o^{(i)}\) are the predicted labels of the new model and the old model for input image \(x_i\), and \(N\) is the number of samples in the test set \(S_{test} = \{(x_i, y_i), i = 1..N\}\).

All models in these experiments were trained with batch size 512. On CIFAR100 (ImageNet), the model was trained for 240 (90) epochs, with learning rate decreased by 0.1 every 80 (30) epochs. For CNA, the trade-off \(\lambda\) in Eq. (7) is chosen by validation as 1 for CIFAR100 and 0.2 for ImageNet. To ensure a fair comparison, the hyper-parameters for focal distillation were also chosen through the same validation split of CNA.

We consider the common model update scenario: the new model architecture is larger than that of the old model. We evaluated a variety of architecture changes, including ShuffleNet and ResNet variants. The models were both trained on the same dataset. The results are visualized in Fig. 3. We observe that CNA can consistently reduce the NFR. In particular, the relative NFR reduction compared to the baseline new model is 29.9% on CIFAR100 and 14.1% on ImageNet. On ImageNet, CNA slightly improves the model accuracy from 76.13% to 76.28%. CNA outperforms the baseline new model is 29.9% on CIFAR100 and 14.1% on ImageNet. On ImageNet, CNA slightly improves the model accuracy from 76.13% to 76.28%. CNA outperforms the baseline new model is 29.9% on CIFAR100 and 14.1% on ImageNet. On ImageNet, CNA slightly improves the model accuracy from 76.13% to 76.28%

### 4.3. Ablation Studies

To further understand the performance of CNA, we conducted a series of model distillation ablation studies. The source/target model is ResNet56/ResNet20 on CIFAR100 and ResNet34/ResNet18 on ImageNet. The default settings are: temperature \(\tau = 0.01\), number of neighbors \(K = 1\), number of MLP is 0 and batch size is 512 (1024) for CIFAR100 (ImageNet).

**Batch Size.** The effect of batch size is investigated in Tab. 4. It can be found that the CNA algorithm is quite robust to different batch sizes on CIFAR100, as long as the batch size is not smaller than 128. But the performance decreases when the batch size becomes smaller on ImageNet. This is probably because there are 1,000 classes for ImageNet and it is possible there is no very close neighbor in a single batch if the batch size is too small. Relatively large batch size is preferred for CNA to better preserve the local structure.

**Temperature** \(\tau\) was ablated in Tab. 6. It shows the best choice is around \(\tau = 0.01\). When it is decreased or increased too much, the performances drop. This temperature is also robust to different datasets.

**Number of neighbors** \(K\) in Eq. (6) was ablated in Tab. 7. On both datasets, \(K = 1\) performs considerably well, but the performances decrease when more neighbors were counted in the loss function of Eq. (6). This is probably because the contrastive loss formulation (Eq. (6)) is curated for single pair contrast. Directly including the other neighbors without considering their further structure information, e.g. neighbor ranking, from the old model may impose inaccurate neighborhood regulation on the new model, thus degrading the performance.

**Number of MLPs.** The hidden MLP layers have been shown to be very helpful for representation learning [6,14]. Results from investigations of its effect on CNA are shown in Tab. 5. It shows that the hidden MLP layer does not help in CNA. The possible reason could be that the goal of CNA, maintaining the local data structure, is different from the representation learning [6,14].

### 5. Conclusion

In this paper, we proposed a new method, contrastive neighborhood alignment (CNA), that preserves the local structure of feature spaces between models. The effectiveness of CNA is illustrated on three problems: manifold learning, where the topology of the original data is maintained in a low-dimensional space using an inductive model, model distillation, where a compact student is trained to mimic a larger one, and model upgrade, where the new model is more powerful than the old one. Existing methods in model distillation are primarily focused on matching the output predictions/logits for the pair of models in question whereas CNA is motivated differently by preserv-
ing the local neighborhood structures of the samples in the representation spaces. The instance-level contrastive loss in CNA is empirically shown to work harmoniously with the standard cross-entropy loss.

**Limitations:** The concept of aligning the local neighborhoods is intuitive but its performance gain in model distillation still has room to improve. Nonetheless, CNA provides a new means for preserving the integrity of the model by matching the feature manifold using a contrastive term that has not been previously explored.

**Potential Negative Societal Impacts:** CNA may accidentally transfer the bias in the source feature embedding [5] to the target model. As a result it may unintentionally amplify these biases when deploying the model. Selecting unbiased source model or applying debiasing algorithm to the learned new model can mitigate this negative effect.

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