Gradient Regularized Contrastive Learning for Continual Domain Adaptation

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Abstract

Human beings can quickly adapt to environmental changes by leveraging learning experience. However, the poor ability of adapting to dynamic environments remains a major challenge for AI models. To better understand this issue, we study the problem of continual domain adaptation, where the model is presented with a labeled source domain and a sequence of unlabeled target domains. There are two major obstacles in this problem: domain shifts and catastrophic forgetting. In this work, we propose Gradient Regularized Contrastive Learning to solve the above obstacles. At the core of our method, gradient regularization plays two key roles: (1) enforces the gradient of contrastive loss not to increase the supervised training loss on the source domain, which maintains the discriminative power of learned features; (2) regularizes the gradient update on the new domain not to increase the classification loss on the old target domains, which enables the model to adapt to an in-coming target domain while preserving the performance of previously observed domains. Hence our method can jointly learn both semantically discriminative and domain-invariant features with labeled source domain and unlabeled target domains. The experiments on Digits, DomainNet and Office-Caltech benchmarks demonstrate the strong performance of our approach when compared to the state-of-the-art.

1 Introduction

Deep learning has shown great generalization power on various benchmarks when the training and testing data are drawn from the same distribution. However, the model trained on an existing benchmark cannot generalize effectively to a new scenario due to the well-known domain shift problem. The existence of domain shift hinders the deployment of deep learning models in the open environment of the real-world. Extensive Domain Adaptation (DA) methods [1, 2, 3, 4, 5] have been proposed to enable models to generalize from a label-rich source domain to an unlabeled target domain. Most of the literature of domain adaptation focus on adapting from source domain to one target domain [1, 2, 3, 4, 5] or multiple target domains [7, 8, 9]. However, many machine learning models deployed in the real-world are exposed to non-stationary situations where different domains are acquired sequentially and their distribution varies over time, such as deep learning models in autonomous vehicles. When meeting the scenario where target domains are multiple and are coming sequentially, existing DA methods collapse because the models may quickly adapt to new domains and easily forget knowledge on old target domains. The killer defect, which is known as catastrophic forgetting, prevents most DA algorithms being put into practice.

This work studies the problem of continual domain adaptation that the models are required to continually adapt to new target domains without harming performances on the previously observed domains. Previous continual DA methods [10, 11] require priors about domain labels to conduct...
Figure 1: Illustration of GRCL. In Fig.(a)(b) the shape denotes class and color denotes domain. The contrastive loss pushes target samples towards its similar ones in the source domain. However, it inevitably pushes some discriminative features towards the instance features of lower discriminative power (purple area), as the contrastive loss only captures the visual similarity while ignoring the semantics. Such a problem is verified by the severe performance degradation on the source domain (Fig.(c)). GRCL regularizes the model update not to increase the loss on source domain (black arrow), that maintains the discriminative power of learned features.

domain adversarial training or build a graph of inter-domain relationships. However these priors may not be accessible in practice, i.e. the target domain is compounded with multiple subdomains. Besides, the existing method [10] applies naive sample replay to avoid catastrophic forgetting, which still suffers from the large negative backward transfer.

In this work, we propose gradient regularized contrastive learning (GRCL) to tackle “domain shifts” and “catastrophic forgetting” in a unified framework. At the core of GRCL, gradient regularization plays two key roles: (1) enforces the gradient of contrastive loss not to increase the supervised training loss on the source domain, which maintains the discriminative power of source features, and in turn improves the target features learned by contrastive loss; (2) regularizes the gradient update on the new domain not to increase the classification loss on the domain memory, which enables the model to adapt to an in-coming target domain while preserving the performance of previously observed domains. Hence GRCL can jointly learn semantically discriminative and domain-invariant features, without reliance on priors of domain-related information.

Specifically, we construct a domain memory to store a subset of image samples from each domain. GRCL leverages the contrastive loss to jointly learn image representation with the domain memory and the incoming target domain. Because the instances belong to the same category exhibit similar appearances, the contrast loss encourages the model to push the target samples towards the samples in the domain memory that belong to the same class, in feature space. Thus different domain inputs belong to the same category will be aligned in the feature space, resulting in domain-invariant image representation. However, simply combining the contrastive learning and supervised learning (with source domain data) as a multi-task learning objective could hurt the discriminative power of learned features, due to the conflict between contrastive loss and cross-entropy loss. As shown in the purple area of Fig.1(b), the contrastive loss inevitably pushes some discriminative features towards the instance features of less discriminative power, as the contrastive loss only captures the visual similarity while ignoring the semantics. Such a problem is empirically verified by the experimental results in section 4.2.2. To solve this conflict, we enforce the gradient of contrastive loss not to increase the cross-entropy loss on the source domain, which maintains the discriminative power of source features. Since the source instance features act as the anchors for the target instances in contrastive learning, it also improves the quality of learned target features. To overcome “catastrophic forgetting”, we construct an additional set of constraints in which each constraint is imposed to enforce the classification loss of each domain-specific memory never increasing.

To summarize, our contributions are as follows: (1) We propose gradient regularized contrastive learning to jointly learn both discriminative and domain-invariant representation without reliance on priors of domain labels. At the core of our method, gradient regularization performs two key functions: maintaining the semantically discriminative power of learned features and overcoming catastrophic forgetting. (2) The experiments on multiple continue domain adaptation benchmarks demonstrate the strong performance of our method when compared to the state-of-the-art.
2 Problem Formulation and Evaluation Metric

Let $D_s = \{(x_i^s, y_i^s)\}_{i=1}^{n_s}$ be the labeled dataset of source domain, where each example $(x_i^s, y_i^s)$ is composed of an image $x_i^s \in \mathcal{X}$ and its label $y_i^s \in \mathcal{Y}$. Continue domain adaptation defines a sequence of adaptation tasks $T = \{T_1, T_2, \ldots, T_N\}$. Different domains have a common label space $\mathcal{Y}$ but distinct data distributions. On $t$-th task $T_t$, there is an unlabeled target domain dataset $D_t = \{x_i^t\}_{i=1}^{n_t}$. The goal is to learn a label prediction model $f$ that can generalize well on multiple target domains $\{D_1, \ldots, D_N\}$. Note that data from different domains in general follow different distributions.

We propose two metrics to evaluate the model adapting over a stream of target domains, namely average accuracy (ACC) and average backward transfer (BWT). After the model finishes the training of adaptation task $T_i$, we evaluate its individual performance on the testing set of the current and all the previously observed domains $D_k^{\text{test}}(\forall k \leq i)$. Let $R_{i,j}$ denote the test accuracy of the model on the domain $D_j$ after finishing adapting to domain $D_i$. We use $D_0$ to denote the source domain. ACC and BCT can be calculated as

$$
\text{ACC} = \frac{1}{N} \sum_{i=0}^{N} R_{N,i} \quad \text{BWT} = \frac{1}{N - 1} \sum_{i=1}^{N-1} R_{N,i} - R_{i,i}.
$$

The ACC represents the average performance over all domains when the model has finished the last adaptation task. And BCT indicates the influence that adapting to domain $D_t$ on the previously observed domain $D_{k<t}$. The negative BWT indicates that adapting to a new domain decreases the performance on previous domains. The larger these two metrics, the better the model.

3 Method

3.1 Gradient Regularized Contrastive Learning

Contrastive learning \cite{12, 13, 14} has recently shown the great capability of mapping images to an embedding space, where similar images are close together and dissimilar images are far apart. Inspired by this, we utilize the contrastive loss to push the target instance towards the source instances that own similar appearances with target input. Thus the same category instances that are apparently similar but from different domains are aligned in the feature space, resulting in domain-invariant features. Specifically, we first define an episodic memory $M_t$, which stores a subset of observed images from target domain $D_t$. When the model is adapting to $t$-th domain, we have a domain memory $\mathcal{M} = \cup_{i=1}^{t-1} M_i$, that is a union of all past episodic memories.

Let $f_{t-1}$ be the model finishing the adaptation training on domain $D_{t-1}$. We construct a domain-affiliate feature bank $B_t = \{k(x), \forall x \in D_t \cup \mathcal{M} \cup D_1\}$ to store the instance features from both source and various target domains (see Fig. \[2\]). Here, $k(x)$ is a compact representation of the input $x$, which is initialized by $k(x) = g(f(x, \theta_{t-1}))$ and normalized so that $\|k(x)\|^2 = 1$. We choose $g(\cdot)$ to be a 2-layer MLP $g(z) = W_2 \sigma(W_1 z)$ that maps the semantic features to a low-dimensional vector of $\text{dim} = 128$. Given an query input $q = k(x)$, we assume there is a single positive key $k_+$ that $q$ matches. $k_+$ is designed as $g(f(T(x), \theta))$, where $T(\cdot)$ denotes the data augmentation. With similarity measured by dot product, we consider the contrastive loss function of InfoNCE \cite{15}:

$$
\mathcal{L}_{q(x), k^+, k^-} = -\log \frac{\exp(q \cdot k^+ / \tau)}{\exp(q \cdot k^+ / \tau) + \sum_{k^- \in B_t} \exp(q \cdot k^- / \tau)},
$$

where $k^-$ represents the negative key for $q$, and $\tau$ is the temperature. During the training, we update the sampled keys with the up-to-date model $f_\theta$, by $k \leftarrow m \cdot k^{i-1} + (1-m) k^i$, which $i$ indicates the training iteration and $m$ is the momentum. Then the adaptation objective becomes a multi-task of supervised training loss on $D_s$ and contrastive learning loss on the feature bank $B_t$:

$$
\min_{\theta_t} \mathcal{L} = \mathcal{L}_{ce}(\theta_t, D_s) + \lambda \mathcal{L}_{\text{contrast}}(\theta_t, B_t)
= \frac{1}{|D_s|} \sum_{(x,y) \in D_s} CE(f(x; \theta_t), y) + \lambda \frac{1}{|B_t|} \sum_{x \in D_s \cup \mathcal{M} \cup D_1} \mathcal{L}_{q(x), k^+, k^-},
$$

where $CE(\cdot)$ is the cross-entropy loss.
Figure 2: Gradient Regularized Contrastive Learning. The gradient regularization (right) is utilized to enforce the gradient of contrastive loss not to increase the cross-entropy loss, which maintains the discriminative power of feature learned by contrastive learning.

where \( L_{ce} \) is the cross entropy loss on source domain \( D_s \). \( b_s, b_t \) denote the mini-batch of samples from \( D_s \) and union of \( D_s \cup M \cup D_t \) respectively. \( \lambda \) is the hyper-parameter to trade off the two losses.

However, our experiments show that the multi-task objective of Eq. 2 only brings marginal improvements on the target domain, as shown in Fig. 1 (c). We hypothesize the problem raised from the conflict of two objectives, namely cross-entropy loss and contrastive loss. As illustrated in the purple area in Fig. 1(b), the discriminative instance features could be pushed towards less-discriminative instance features, because of the apparent similarity. This conflict is verified by the experiments that contrast loss degrades the model performance on the source domain (see Section 4.2.2), suggesting hurting the discriminative power of image features from the source domain. Since the source instance features act as the anchors for the target instances in contrastive learning, the conflict may impose an undesirable influence on the discriminative power of image features from the target domain.

To solve the conflict between \( L_{contrast} \) and \( L_{ce} \), we enforce the regularization that the \( L_{ce} \) on the source domain should not increase when minimizing the \( L_{contrast} \). Then the final domain adaptation objective with constraints can be rephrased as:

\[
\min_{\theta_t} \quad L_{contrast}(\theta_t, B_t) \quad \text{subject to} \quad \langle g_s, g_t \rangle \geq 0, \quad (3)
\]

where \( \langle g_t, g_s \rangle \) is the inner product of gradient of loss \( L_{contrast} \) and \( L_{ce} \) w.r.t. model parameters:

\[
\langle g_s, g_t \rangle := \left\langle \frac{\partial L_{ce}(\theta_t, D_s)}{\partial \theta_t}, \frac{\partial L_{contrast}(\theta_t, B_t)}{\partial \theta_t} \right\rangle \geq 0. \quad (4)
\]

And \( \theta_t \) is initialized with the model trained on the source domain with labels. As illustrated in Fig 2(right), if the constraint of Eq. 4 is satisfied, then the parameter update \( g_t \) is unlikely to hurt the discriminative power of image features from the source domain, as it does not increase the cross-entropy loss on the source domain. If the violations occur, we propose to project the \( g_t \) to the closest gradient \( \hat{g}_t \) satisfying the constraint of Eq. 4. Thus GRCL enjoys the benefits of semantically discriminative features offered by the gradient regularization and domain-invariant features learned by contrastive loss.

### 3.2 Overcoming Catastrophic Forgetting

In this section, we extend the GRCL with additional constraints to overcome "catastrophic forgetting", in which each constraint is imposed to enforce the classification loss of each domain-specific memory never increasing. Mathematically, the constraints can be formulated as:

\[
L_{ce}(\theta_t, M_k) \leq L_{ce}(\theta_{t-1}, M_k) \quad \text{for all} \quad k < t. \quad (5)
\]

where \( \theta_{t-1} \) is the model parameters at the end of adapting task on \( D_{t-1} \). While Eq. 5 effectively permits positive backward transfer of GRCL, it comes at a huge computation burden at training time. At each training step, we need to solve the \( t-1 \) inequality constraints of all episodic memories. It
will become prohibitive when the size of $M_k$ and number of adaptation tasks are large. Alternatively, we propose a much efficient way to approximate the Eq.5 by

$$L_{ce}(\theta_t, M) \leq L_{ce}(\theta_{t-1}, M),$$

where $M = \bigcup_{i=1}^{t-1} M_i$ is the domain memory. Instead of computing the loss on each individual old domain, Eq.6 only computes the loss with the sampled batch of images from domain memory $M$.

For computing $L_{ce}(\theta_t, M)$, we adopt standard $k$-means clustering algorithm [16] to generate pseudo labels with a pre-trained model obtained from previous domain adaptation task. Combining the adaptation objective of Eq.3 and against-forgetting objective of Eq.6, we have the final objective for continue domain adaptation:

$$\min_{\theta_t} L_{\text{contrast}}(\theta_t, B_t)$$

subject to $\langle g_t, g_s \rangle \geq 0$

$$L_{ce}(\theta_t, M) \leq L_{ce}(\theta_{t-1}, M).$$

The first constraint is to facilitate the contrastive learning to learn discriminative features. The second constraint ensures the average loss on previously observed domains does not increase, which enforces the model not to forget acquired knowledge on preceding domains. Mathematically, we want to find the gradient update $\hat{g}_t$ satisfying:

$$\min_{\hat{g}_t} \frac{1}{2} \| g_t - \hat{g}_t \|^2_2$$

subject to $\langle \hat{g}_t, g_s \rangle \geq 0$

$\langle \hat{g}_t, g_{dm} \rangle \geq 0,$

where $g_{dm}$ is the gradient computed using a batch of random samples from the domain memory $M$. Eq.8 is a quadratic program (QP) on $P$ variables (the number of parameters in the neural network), which could be measured in millions for deep learning models. To solve Eq.8 efficiently, we work in the dual space of Eq.8 which results in much smaller QP with only 2 variables:

$$\min_u \frac{1}{2} u^T G G^T u + g_t^T G^T u$$

subject to $u \geq 0,$

where $G = -(g_s, g_{dm}) \in \mathbb{R}^{2 \times P}$ and we discard the constant term of $g_t^T g_t$. The formal proof of Eq.8 is provided in Appendix B. Once the solution $u^*$ to Eq.9 is found, we can solve the Eq.8 with the gradient update of $\hat{g}_t = G^T u^* + g_t$. Appendix A summarizes the training protocol of GRCL.

4 Experiments

4.1 Dataset and Methods

Digits includes five digits datasets (MNIST [17], MNIST-M [18], USPS [19], SynNum [18] and SVHN [20]). Each domain has 7,500 images for training and 1,500 images for testing. We consider a continual domain adaptation problem of SynNum $\rightarrow$ MNIST $\rightarrow$ MNIST-M $\rightarrow$ USPS $\rightarrow$ SVHN.

DomainNet [21] is one of the largest domain adaptation datasets with approximately 0.6 million images distributed among 345 categories. Each domain randomly selects 40,000 images for training and 8,000 images for testing. Five different domains from DomainNet are used to build a continual domain adaptation task as Clipart $\rightarrow$ Real $\rightarrow$ Infograph $\rightarrow$ Sketch $\rightarrow$ Painting.

Office-Caltech [22] includes 10 common categories shared by Office-31 [23] and Caltech-256 [24] datasets. Office-31 dataset contains three domains: DSLR, Amazon and WebCam, which represent the images that are collected in different environments respectively. We consider a continual domain adaptation problem of DSLR $\rightarrow$ Amazon $\rightarrow$ WebCam $\rightarrow$ Caltech.

We compare GRCL with five alternatives, including (1) DANN [1], a classic domain adversarial training based method; (2) MCD [4], maximizing the classifier discrepancy to reduce domain gap; (3) DADA [6], disentangling the domain-specific features from category identity; (4) CUA [10], adopting
Figure 3: ACC and BWT on three continual domain adaptation benchmarks.

For fair comparison with previous state-of-the-art, we adopt LeNet-5 [17] on Digits, ResNet-50 [25] on DomainNet, and ResNet-18 [25] on Office-Caltech benchmarks. Each domain has the same number of training and testing images. For contrastive learning, we use a batch size of 256, feature update momentum of 0.5, number of negatives as 1024, training schedule of 240 epochs. The MLP head uses a hidden dimension of 2048. Following [12, 13], the temperature \( \tau \) in Eq.1 is set as 0.07.

For data augmentation, we use random color jittering, Gaussian blur and random horizontal flip. And the image samples in the episodic memory are selected by the model predictions with top-1024 confidence. For methods using memory, CUA, GRA and GRCL use exactly the same size of episodic memory for each domain and same \( k \)-means algorithm to generate pseudo labels.

4.2 Experimental Results

Figure 4: Evolution of classification accuracy on the first target domain as more domains are observed. Existing methods exhibit significant performance degradation due to catastrophic forgetting.

Fig.3 shows the results on three benchmarks. The larger the average accuracy (ACC) and backward transfer (BWT) the better the model. When the model has finished the training on the last target domain, we report the ACC over all observed domains. As shown in Fig.3, GRCL consistently achieves better ACC across three benchmarks, suggesting that the model trained with GRCL owns the best generalization capability across domains. Unsurprisingly, most methods exhibit lower negative BWT, as catastrophic forgetting exists. The methods using memory (CUA, GRA, GRCL) performs
Table 1: ACC and BWT on three continue domain adaptation benchmarks.

| Methods | Digits | DomainNet | Office-Caltech |
|---------|--------|-----------|----------------|
|         | ACC    | BWT       | ACC            | BWT            |
| DANN [1]| 74.56 ± 0.14 | -11.37 ± 0.09 | 30.18 ± 0.13  | -10.27 ± 0.07  |
| MCD [4] | 76.40 ± 0.24 | -10.90 ± 0.11 | 31.68 ± 0.20  | -10.36 ± 0.15  |
| DADA [6]| 77.30 ± 0.19 | -11.40 ± 0.04 | 32.14 ± 0.14  | -8.67 ± 0.09   |
| CUA [10]| 82.12 ± 0.18 | -6.10 ± 0.12  | 34.22 ± 0.16  | -5.53 ± 0.14   |
| GRA     | 84.10 ± 0.15 | -0.93 ± 0.10  | 35.84 ± 0.19  | -1.15 ± 0.16   |
| GRCL    | 85.34 ± 0.10 | -1.0 ± 0.03   | 37.74 ± 0.13  | -0.67 ± 0.12   |

better than the other methods without memory (DANN, MCD, DADA), especially on the BWT metric. These results highlight the importance of memory in the continual DA problem.

Among the memory-based methods, GRA and GRCL achieve significantly better BWT on three benchmarks, suggesting the effectiveness of gradient constraints for combating catastrophic forgetting. GRCL consistently achieves better ACC than GRA across all benchmarks. It partially because that GRCL utilizes all the samples from domain memory (cached the samples from all previously observed domains) to jointly learn representation, while GRA only uses source domain and current target domain to learn features. Fig.4 depicts the evolution of classification accuracy on the first target domain as more domains are observed. GRCL consistently exhibits minimal forgetting and even positive backward transfer on Office-Caltech benchmark. Table 1 summarizes the detailed results for all methods on three continual DA benchmarks. Each entry in the Table 1 represents the mean and standard deviation of classification accuracy of five runs in corresponding experiments.

4.2.1 Importance of Memory Size and Training Schedule

Table 2: ACC as a function of memory size.

| memory size | 256  | 512  | 1024 | 2048 |
|-------------|------|------|------|------|
| Digits      | 83.00 | 84.12 | 85.34 | 85.41 |
| DomainNet   | 33.28 | 35.75 | 37.74 | 37.83 |

Table 2 shows the ACC of GRCL under various memory sizes per domain. The ACC benefits from a larger memory size. Because larger domain memory provides more negative samples for contrastive learning, resulting in better self-supervised representation learning. As the Office-Caltech dataset only has 100 training samples per domain, it is not applicable to do the ablation of memory sizes.

Table 3: ACC as a function of training epoch.

| training epoch | 120 | 180 | 240 | 300 |
|---------------|-----|-----|-----|-----|
| Digits        | 80.10 | 83.46 | 85.34 | 85.38 |
| DomainNet     | 34.80 | 36.50 | 37.74 | 38.16 |
| Office-Caltech| 80.93 | 84.70 | 87.23 | 87.28 |

Table 3 shows the ACC of GRCL with different training schedules. Because contrastive learning naturally benefits from longer training schedules [13], GRCL consistently got improvements of ACC as more training epochs are adopted. But the performance gain soon saturates after 240 epochs.

4.2.2 Importance of Gradient Regularization in GRCL

In this section, we evaluate the effect of gradient regularization of GRCL on one target domain setting. We compare three different methods: (1) source only, which the model is supervised trained on source domain; (2) Multi-task, using multi-task objective of Eq.2; (3) GRCL. The λ in Eq.2 uses the best value obtained via grid search on each target domain. The SynNum, Clipart and DSLR are used as the source domain for Digits, DomainNet and Office-Caltech dataset respectively. We report the averaged classification accuracy on the different target domains. As shown in Fig.5, Multi-task improves the performance on the target domain over the baseline of source only method. Because of the conflicts between cross-entropy loss and contrast loss. Multi-task trained model sacrifices the performance of original source domain, which in turn hurts the discriminative power of image features of the target domain. Benefiting from the gradient regularization, GRCL enjoys the domain-invariant feature learning brought by contrast loss, and semantically discriminative feature provided by cross-entropy loss, which together helps it achieve the better classification accuracy on the target domain.
5 Related Works

Continual domain adaptation [10] adopts adversarial training to align different domain distributions and reuse self-labeled samples of previous domains to retain classification performance. [11] propose AdaGraph to encode inter-domain relationships with domain metadata (i.e., the viewpoint of an image captured), and utilize it produce domain-specific BN parameters. However, existing methods have two limitations: (1) [10] requires domain labels to do domain adversarial training and [11] requires additional metadata as prior to build the domain relation graph, which may not accessible in practice. In contrast, GRCL leverages self-supervised learning to learn domain-invariant representation, which does not reacquire priors of domain-related information. (2) [10] uses sample replay to avoid catastrophic forgetting. However, the simple buffer-replay based methods still suffer from the negative transfer, as shown by [26]. In contrast, our method explicitly constraints domain adaptation learning on the new domain not to increase the loss on previous domains. Thus it theoretically permits positive backward transfer that existing method [26] does not support.

Contrastive learning has been a powerful self-supervised learning method to learn semantic image representation that can be transferred to downstream vision recognition tasks. It utilizes a contrastive loss to encourage the model to embed similar images closer to each other while dissimilar images separate in the feature space. Different contrastive learning methods vary in the strategy to generate positive and negative image pairs for each input. For example, [12] samples the images pairs from a memory bank, [13, 27] adopt a momentum encoder to generate the image pairs and [28, 14] produce the image pairs using the current batch of images. In this work, we utilize the contrastive learning to jointly learn domain-invariant image representation and the gradient regularization is proposed to maintain the discriminative power of learned representation.

Continual learning addresses the catastrophic forgetting in a sequence of supervised learning tasks. One representative technique is using episodic memory [26, 29] to store some training samples of old tasks, which are used to overcome catastrophic forgetting via constrained optimization. In contrast to continual learning that considers a sequence of supervised learning tasks without domain shift problem, continual domain adaptation aims to solve a sequence unsupervised domain adaptation tasks under domain shifts. Hence continual DA not only requires the learner to overcome catastrophic forgetting like lifelong learning dose but also needs the learner to adapt the novel target domain with varying data distributions.

6 Conclusion

This work studies the problem of continual DA, which is one major obstacle in the deployment of modern AI models. We propose Gradient Regularized Contrastive Learning (GRCL) to joint learn both discriminative and domain-invariant representations. At the core of our method, gradient regularization maintains the discriminative power of feature learned by contrastive loss and overcomes catastrophic forgetting in the continual adaptation process. Our experiments demonstrate the competitive performance of GRCL against the state-of-the-art.

Figure 5: Comparison among Source only, Multi-task and GRCL. The performance on target represents the averaged accuracy over all different target domains.
7 Broader Impact

Deep neural networks have achieved great success on many supervised learning tasks, where enormous data annotations are available and the data distribution does not change over time. However, it remains challenging for deep neural networks to adapt to novel domains, whose data distributions change over time and the data annotations may not be available. The positive impact of this work is providing a method that enables continually adapt to environmental changes by leveraging past learning experience. At the same time, this work may increase the risk of data privacy because now more unlabeled data can be used to improve the AI models. Recently, many privacy-preserving training methods have been explored to improve data privacy, such as federated learning and SecureML. In the future, these privacy-preserving methods can be combined with a continual domain adaptation approach to improve AI models while preserving data privacy.

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Appendix A  Algorithm of Gradient Regularized Contrastive Learning

Algorithm 1 GRCL for Continual Domain Adaptation

```
procedure Train(θ, Ds, {D1, ..., DT})
    M ← {}
    B1 ← BuildFeatureBank(θ, D1, M)
    for t = 1, ..., T do
        for (x, i) in Ds ∪ M ∪ Dt do
            gt ← ∇Lcontrast(θ, Bt)
            gs ← ∇Lce(θ, Ds)
            UpdateKey(x, i, Bt)
            (x', y') ∼ M
            gm ← ∇Lce(θ, (x', y'))
            ̃gt ← Solve(gt, gs, gm), see Eq.8
            θ ← θ − η ̃gt
        end for
        Bt+1 ← BuildFeatureBank(θ, Dt, M)
        M ← UpdateMemory(θ, Dt, M)
    end for
    return θ
end procedure

procedure UpdateMemory(θ, Dt, M)
    Dt ← run k-means on Dt
    M ← M ∪ Dt
    return M
end procedure

procedure BuildFeatureBank(θ, Dt, M)
    Bt+1 ← {}
    for x in Ds ∪ M ∪ Dt do
        k = g(f(x; θ))
        k = k∥k∥2
        Bt+1 ← Bt ∪ {k}
    end for
    return Bt+1
end procedure

procedure UpdateKey(x, i)
    k(x) ← m · k(x) + (1 − m)k'(x)
end procedure
```
Appendix B  Quadratic Program of Equation (8)

Proof The optimization objective in the Equation (8) of the main paper is:

\[
\begin{aligned}
\min_{\hat{g}_t} & \quad \frac{1}{2} \|g_t - \hat{g}_t\|^2_2 \\
\text{subject to} & \quad \langle \hat{g}_t, g_s \rangle \geq 0 \\
& \quad \langle \hat{g}_t, g_{dm} \rangle \geq 0.
\end{aligned}
\]  

(10)

Replacing \( \hat{g}_t \) with \( z \) and discarding the constant term of \( g_t^T g_t \), Equation (10) can be rephrased as

\[
\begin{aligned}
\min_{z} & \quad \frac{1}{2} z^T z - g_t^T z \\
\text{subject to} & \quad Gz \geq 0,
\end{aligned}
\]  

(11)

where \( G = -(g_s, g_{dm}) \in \mathbb{R}^{2 \times P} \) (\( P \) is the number of parameters in the model). The Lagrangian of Equation (11) can be written as:

\[
\mathcal{L}(z, u) = \frac{1}{2} z^T z - g_t^T z - u^T Gz,
\]  

(12)

where \( u \in \mathbb{R}^{2 \times 1} \geq 0 \). Defining the dual of Equation (12) as:

\[
Q(u) = \inf_z \mathcal{L}(z, u).
\]  

(13)

We can find the value \( z^\ast \) that minimizes the \( \mathcal{L}(z, u) \) by setting the derivatives of \( \nabla_z \mathcal{L}(z, u) \) to zero:

\[
z^\ast = G^T u + g_t.
\]  

(14)

Equation (13) can be simplified by substituting the value of \( z^\ast \):

\[
Q(u) = -\frac{1}{2} u^T G G^T u - g_t^T G^T u.
\]  

(15)

So the Lagrangian dual of Equation (10) becomes

\[
\begin{aligned}
\min_u & \quad \frac{1}{2} u^T G G^T u + g_t^T G^T u \\
\text{subject to} & \quad u \geq 0.
\end{aligned}
\]  

(16)