Generation for adaption: a Gan-based approach for 3D Domain Adaption in Point Cloud

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Abstract

Recent deep networks have achieved good performance on a variety of 3d points classification tasks. However, these models often face challenges in “wild tasks”. There are considerable differences between the labeled training/source data collected by one Lidar and unseen test/target data collected by a different Lidar. Unsupervised domain adaptation (UDA) seeks to overcome such a problem without target domain labels. Instead of aligning features between source data and target data, we propose a method that use a Generative adversarial network to generate synthetic data from the source domain so that the output is close to the target domain. Experiments show that our approach performs better than other state-of-the-art UDA methods in three popular 3D object/scene datasets (i.e., ModelNet, ShapeNet and ScanNet) for cross-domain 3D objects classification.

1. Introduction

Deep learning with 3D point cloud data has achieved significant outcomes in different tasks. Classification is the most fundamental task [14]. Despite their impressive success, a Deep Neural Network (DNN) requires a large amount of labeled data for training and labeling them is time-consuming and expensive. Since point clouds, data captured with different sensors or varied mounting positions exhibit a significant shift in their input data distribution, trained DNN model’s performance may significantly decrease in another point clouds dataset.

Domain adaptation (DA) tries to build a model by utilizing the labeled data from a source domain, which can generalize the target domain well. Some of the existing DA methods have focused on mapping features into a shared subspace or minimizing instance-level distances such as MMD [2], CORAL [17]. Other adversarial-training DA methods, like DANN [7], ADDA [18], MCD [16] etc. have tried to use adversarial-training to select domain invariant features during training so that the trained model could perform better in the target domain. PointDan [15] designs a Self-Adaptive Node Construction for aligning 3D local features in point cloud data. A recent work [21] built a DA method that upsamples the source domain data into a canonical domain and trains a semantic segmentation network over the canonical domain.

Our approach chooses to generate synthetic data from a source domain according to the target domain data pattern. Unlike other adversarial-training DA methods, we can fully utilize the advantage of adversarial-training by generating synthetic data while keeping the label of the source domain. Our model architecture consists of three parts: a generator, a discriminator, and a feature encoder/decoder. We have two inputs for the generator, despite the encoded feature of input points cloud, we have a latent code $z$ sampled from standard Gaussian distribution as a condition input. We can generate multi possible output from a single input. [19] prove that this design can improve the quality of output object from the generator. For the encoder we use Point transformer structure [8] and decoder use a 3-layer MLP. Similar to D2GAN [13] we have an additional discriminator, a classifier to further enhance the generator. Extensive experiments with different pairs of a dataset in cross-domain 3D objects classification task show that our approach 2.6% better than PointDan on average, 2.8% better than MCD, and 4.6% better than ADDA.

The rest of the paper is organized as follows. Section 2 mainly introduce our model’s network structure and loss function. Section 3 shows implementation details and quantitative experiment results. Finally, Section 4 presents our
conclusions.

2. Method

This paper proposes a method to overcome the domain gap between different point cloud datasets. We propose a generative model, which takes a point cloud from the source dataset as input first and then tries to maintain the shape of an object while keeping the label information when generating the synthetic object according to the target domain dataset’s pattern. The objective of this source to target domain adaption is that classification could learn the distribution of point cloud in target domain and perform better in the test of target dataset.

As Fig. 2 shows in the training source domain object and target domain object will go through a shared encoder. Liker most GANs, the encoded features will be sent to a discriminator and, the discriminator tries to distinguish features from source domain or target domain. Following the idea in [10] of adding multimodal information to the model, we also have Gaussian samples $z$ and encoder $E_z$ for latent condition input to the generator. To force the generator to use the Gaussian samples $z$, we introduce a VAE encoder to recover $z$ from the synthetic output. Besides, as in [10], to enhance the quality of output object from $G$, we have an additional discriminator, a classifier $C$ in training the model. Below, we explain our model in more detail.

2.1. Definition and Notations

We consider an unsupervised domain adaptation (UDA) setting. A point cloud from source domain is represented as $(X^s \triangleq \{x^s_i\}_{i=1\ldots N}, y^s)$, where $x^s_i \in \mathbb{R}^3$ is a 3D point and $N$ is the number of points in the point cloud; $y \in \{1,2,...,k\}$ is the ground-truth label, where $k$ is the number of classes. In UDA, we have access to a set of labeled LiDAR point clouds, from the source domain and a set of unlabeled LiDAR point clouds a set of unlabeled LiDAR point clouds $(X^t \triangleq \{x^t_i\}_{i=1\ldots N})$ in a target domain. We use classification as the task of domain adaption and denote the classification network as $C_\theta(\cdot) \triangleq \{C_{\theta,j}| j = 1\ldots k\}$, whose input is a point cloud $X$ and output is a probability vector $C_\theta(X)$. Our approach tends to generate synthetic object $X^s$ from $X^t$ and for the generative generative adversarial network we have encoder $E$, decoder $D$, generator $G$ and discriminator $F$. The process is denoted as $X' = D(G(E(X)))$.

2.2. Learning mapping of point cloud to latent space

We obtain feature vector $X_s$ of input point cloud by training an autoencoder. As Fig. 2 show the encoder $E$ consist of 4 self-attention layer [8]. The object $X^s$ from source dataset is encoded as feature vector $X_s$ and decoder $D$ reconstruct object $X$ from latent feature vector $X_s$. The encoder-decoders are trained with reconstruction loss, and we choose Earth Mover’s Distance (EMD) to measure the distance between reconstructed object $\tilde{X}$ and input object $X^s$.

$$L^{\text{recon}} = d_{\text{EMD}}(X^s, D(E(X^s)),$$ (1)

As for the object $X^t$ from the target dataset, instead of training another autoencoder for target domain, we directly feed $X^t$ to $E$ because in [5] is proved this way get better performance in subsequent adversarial training.

![Figure 2. The structure of encoder](image)

2.3. Multimodal mapping for latent space

Like most of the generative adversarial networks, we set a min-max game between generator and discriminator. The generator is trained to fool the discriminator that the discriminator fails to tell if the latent vector comes from the source domain $X^s$ or target domain $X^t$. The Variational Autoencoder (VAE) is trained to model the multimodal distribution of possible output objects and further encode synthetic objects to recover latent input vector, encouraging the use of conditional mode input.

Formally, the latent representation of the source domain input $x_s = E_{AE}(X^s)$, along with random sampled variable $z$ from a standard Gaussian distribution $\mathcal{N}(0, I)$. Thus, a latent representation $\hat{x}_t = G(x_s, z)$ will be generated by generator. Then discriminator will try to distinguish between $x_t$ and $x_t = E_{AE}(X^t)$. The encoder part $E_z$ which is the encoder part of VAE will encode the synthetic output $\tilde{X}$, which is decoded from the latent representation $X^t = D_{AE}(\tilde{x}_t)$, to reconstruct the conditional input $z = E_z(\tilde{X})$.

2.4. Train generator with classification loss

The job of discriminator $F$ is to only distinguish the latent representation from source domain or target domain, and there is no guarantee that the synthetic output will be the same class as input object, though we use reconstruction loss during training to make sure the output point set
Figure 3. Illustration of model structure.

will be close to input point set in Earth Mover’s Distance (EMD). So we add a discriminator to utilize label information from the source dataset fully. The classifier $C$ will predict the class of output point set and compare it with the ground truth label in the source dataset. The loss will be backward to the generator so that generator will generate synthetic objects in the same class as input objects from the source dataset.

2.5. Overall loss function and training

To optimize GAN’s output object quality, we set a min-max game between the generator, the discriminator, and the classifier. Given training examples of source domain object $X_s$, and Gaussian samples $z$, we seek to optimize the following training losses over the generator $G$, the discriminator $F$, the encoder $E_z$ and the classifier $C$:

**Adversarial loss.** For training of the generator and discriminator we add adversarial loss and we implement least square GAN [12] for stabilizing the training. Hence, the adversarial losses minimized for the generator and the discriminator are defined as:

$$L_{GAN}^G = \mathbb{E}_{X_s \sim p(X_s)} [F(G(E_{AE}(X_s), z))] - 1]^2,$$

$$L_{GAN}^F = \mathbb{E}_{X_t \sim p(X_t)} [F(E_{AE}(X_t))] - 1]^2,$$

where $X_t \sim p(X_t)$, $X_s \sim p(X_s)$ and $z \sim p(z)$ denotes samples drawn from the set of complete point sets, the set of partial point sets, and $\mathcal{N}(0, I)$.

**Reconstruction loss.** To make the output object similar to the input object in shape, we add a reconstruction loss to encourage the generator to reconstruct the input so that the output object is more likely to be considered the same class as the input object. Here we use Earth Mover’s Distance (EMD) to measure the distance between reconstructed object $\tilde{X}$ and input object $X$.

$$L_{recon}^G = \mathbb{E}_{X_s \sim p(X_s), z \sim p(z)} [d_{EMD}(X_s, D_{AE}(G(E_{AE}(X_s), z)))]$$

**Latent space reconstruction.** A reconstruction loss on the $z$ latent space is also added to force $G$ to use the conditional mode vector $z$ in generating output object:

$$L_{latent}^G = \mathbb{E}_{X_s \sim p(X_s), z \sim p(z)} [\|z - E_z(D_{AE}(G(E_{AE}(X_s), z)))\|_1],$$

**Classification loss.** To restrict the class of output object, we added classification loss to classifier and generator.

$$L_{Cls}^C = \mathbb{E}_{X_s \sim p(X_s), z \sim p(z)} [-K \sum_{k=1}^K l_k \log (G(E_{AE}(X_s), z))]$$

where $l_k$ is the $k$th label among all classes in source dataset. The full objective function for training the domain
transfer network is described as:

$$\arg\min_{G,E,C} \arg\max_F \mathcal{L}_F^{GAN} + \alpha \mathcal{L}_G^{rec} + \beta \mathcal{L}_{G,E}^{latent} + \gamma \mathcal{L}_{G}^{Cls},$$

(8)

where $\alpha$, $\beta$ and $\gamma$ are importance weights for the reconstruction loss, the latent space reconstruction loss and classification loss respectively.

### 2.6. Network implementation

In the experiments, each point cloud object is set to 1024 points. The VAE follows [1, 4]: using a PointNet [14] as the encoder and a 3-layer MLP as the decoder. The autoencoder encodes a point set into a latent vector of fixed dimension $|x| = 128$. Similar to [8], we use 4-layer self-attention layer with MLP as encoder and 3-layer MLP for both generator $G$ and discriminator $F$. Classifier is also using a Pointnet structure. For training the VAE, we use the Adam optimizer [9] with an initial learning rate 0.0005, $\beta_1 = 0.9$ and train 2000 epochs with a batch size of 200. To train the autoencoder we use the Adam optimizer with an initial learning rate 0.0005, $\beta_1 = 0.5$ and train for a maximum of 1000 epochs with a batch size of 32. To train the GAN, we use the Adam optimizer with an initial learning rate 0.0005, $\beta_1 = 0.5$ and train for a maximum of 1000 epochs with a batch size of 50. The classifier used in GAN training was pre-trained on the source dataset with Adam optimizer in an initial learning rate 0.0001 for 200 epochs.

### 3. Experiments

#### 3.1. Datasets

We verify our domain adaption model on three public point cloud datasets shapenet [3], scannet [6] and modelnet [20] and follow the same setting as PointDA-10 [15], we choose 10 common classes among three datasets. The statistic result are shown in Table 1. $M$, $S$ and $S^*$ represent subset of Modelnet, Shapenet and Scannet respectively. We organize six types of adaptation scenarios which are $M \rightarrow S$, $M \rightarrow S^*$, $S \rightarrow M$, $S \rightarrow S^*$, $S^* \rightarrow M$ and $S^* \rightarrow S$.

#### 3.2. Experiments Setup

We choose the PointNet [14] as the backbone of the classifier in evaluation. The learning rate is assigned as 0.0001 under the weight decay 0.0005 and $\alpha, \beta, \gamma$ follow the Table 2. In choosing the hyperparameters, $\alpha$ controls how similar the shape of synthetic output object with the shape of the input object in 3D space, $\beta$ determines how close the synthetic output object with input object in latent space, and $\gamma$ influences how much probability the synthetic object will be considered as same class as input object under classifier. All models have been trained for 200 epochs of batch size 64 in both source domain and synthetic datasets.

#### Baselines:

In our experiments we also compare the our model with a serial of general-purpose UDA methods including: Maximum Mean Discrepancy (MMD) [11], Adversarial Discriminative Domain Adaptation (ADDA) [18].

| Dataset | $\alpha$ | $\beta$ | $\gamma$ |
|---------|---------|---------|---------|
| $M \rightarrow S$ | 0.05 | 0.05 | 0.01 |
| $M \rightarrow S^*$ | 5 | 5 | 0.01 |
| $S \rightarrow S^*$ | 10 | 1 | 0.01 |
| $S \rightarrow M$ | 10 | 1 | 0.01 |
| $S^* \rightarrow M$ | 0.05 | 0.05 | 0.01 |

| Source domain | Synthetic output | Target domain |
|---------------|------------------|--------------|
| Plant | Monitor | Chair |
| Bathhubb | Bed | Bookshelf |
| Cabinet | Lamp | Monitor |
| Plant | Sofa | Total |

| Dataset | Bathhubb | Bed | Bookshelf | Cabinet | Chair | Lamp | Monitor | Plant | Sofa | Total |
|---------|---------|-----|-----------|---------|-------|------|---------|-------|------|-------|
| M       | Train 106 | 515 | 572 | 200 | 889 | 124 | 465 | 240 | 680 | 392 | 4,183 |
| Test | 50 | 100 | 100 | 86 | 100 | 20 | 100 | 100 | 100 | 100 | 856 |
| S       | Train 199 | 167 | 310 | 1,076 | 4,612 | 620 | 762 | 158 | 2,198 | 5,876 | 17,378 |
| Test | 43 | 29 | 50 | 128 | 462 | 232 | 412 | 30 | 359 | 362 | 2,492 |
| S*      | Train 98 | 329 | 464 | 630 | 2,578 | 184 | 210 | 88 | 493 | 1,037 | 6,110 |
| Test | 26 | 85 | 146 | 149 | 801 | 41 | 61 | 25 | 134 | 301 | 1,769 |

Figure 4. Visualization for source domain object, target domain object and synthetic object.
Domain Adversarial Neural Network (DANN) [7], Maximum Classifier Discrepancy (MCD) [16] and PointDAN [15] and In implementation we take the same training policy. w/o Adapt refers to the model trained only by source samples and Supervised means fully supervised method.

As shown from Table 3 our approach can improve all six scenarios. Especially in S* → S and S* → M scenario. Because Among the three different datasets, ScanNet is the most challenging dataset because ScanNet’s point cloud objects are scanned from the real world, the other two datasets are generated from 3D polygonal models. Thus the difference between S* → S and S* → M are more significant from observation and our approach trying to generate synthetic objects which can minimize the gap of points distribution.

**Ablation Study Setup:** We introduced the ablation study that removed the classifier and only kept the generator and discriminator to analyze the classifier’s effects in our Generative Adversarial Network.

**4. Conclusion**

We have proposed a novel approach to unsupervised domain adaptation in the 3D classification task in this work. The basic idea is to transfer training data into the target domain rather than selecting domain invariant feature or implementing feature alignment. In our approach, a Generative Adversarial Network is constructed for domain transfer in 3D point-clouds to perform unsupervised domain adaptation in 3D classification. Our model generates synthetic objects from source domain objects such that the output will have the same shape and label as source domain objects but are constructed according to the pattern of the target domain. In this way classifier trained using the synthetic dataset will perform better in the target domain dataset. To encourage the model to generate an object in the same class as input, we designed a Gan-based framework that takes the classifier as an addition discriminator.

Using extensive experiments involving three datasets and comparing them with five existing DA methods, we have demonstrated our approach’s superiority over the state-of-the-art domain adaptation methods.

**References**

[1] Panos Achlioptas, Olga Diamanti, Ioannis Mitliagkas, and Leonidas Guibas. Learning representations and generative models for 3d point clouds. pages 40–49, 2018.

[2] Karsten M Borgwardt, Arthur Gretton, Malte J Rasch, Hans-Peter Kriegel, Bernhard Schölkopf, and Alex J Smola. Integrating structured biological data by kernel maximum mean discrepancy. Bioinformatics, 22(14):e49–e57, 2006.

[3] Angel X Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, et al. ShapeNet: An information-rich 3D model repository. arXiv preprint arXiv:1512.03012, 2015.

[4] Xuelin Chen, Baoquan Chen, and Niloy J. Mitra. Unpaired point cloud completion on real scans using adversarial training. 2020.

[5] Mitra NJ Chen X, Chen B. Unpaired point cloud completion on real scans using adversarial training. International Conference on Learning Representations (ICLR), 2020.

[6] Angela Dai, Angel X Chang, Manolis Savva, Maciej Halber, Thomas Funkhouser, and Matthias Niener. ScanNet: Richly annotated 3D reconstructions of indoor scenes. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5828–5839, 2017.

[7] Yaroslav Ganin and Victor Lempitsky. Unsupervised domain adaptation by backpropagation. arXiv preprint arXiv:1409.7495, 2014.

[8] Meng-Hao Guo, Jun-Xiong Cai, Zheng-Ning Liu, Tai-Jiang Mu, Ralph R. Martin, and Shi-Min Hu. Pct: Point cloud transformer, 2020.

[9] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

[10] Lanlan Liu, Michael Muehly, Jia Deng, Tomas Pfister, and L-Jia Li. Generative modeling for small-data object detection, 2019.

[11] Mingsheng Long, Jianmin Wang, Guiguang Ding, Jiaguan Sun, and Philip S Yu. Transfer feature learning with joint distribution adaptation. In Proceedings of IEEE International Conference on Computer Vision, 2013.

[12] Xudong Mao, Qing Li, Haoran Xie, Raymond YK Lau, Zhen Wang, and Stephen Paul Smolley. Least squares generative adversarial networks. pages 2794–2802, 2017.

[13] Tu Dinh Nguyen, Trung Le, Hung Vu, and Dinh Phung. Dual discriminator generative adversarial nets, 2017.

[14] Charles R Qi, Hao Su, Kaichun Mo, and Leonidas J Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. Proc. Computer Vision and Pattern Recognition (CVPR), IEEE, 1(2):4, 2017.

[15] Can Qin, Haoxuan You, Lichen Wang, C.-C. Jay Kuo, and Yun Fu. Pointdan: A multi-scale 3d domain adaption network for point cloud representation. In H. Wallach, H. Larochelle, A. Beygelzimer, F. Alch´e-Buc, E. Fox, and R.
Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 7190–7201. Curran Associates, Inc., 2019.

[16] Kuniaki Saito, Kohei Watanabe, Yoshitaka Ushiku, and Tatsuya Harada. Maximum classifier discrepancy for unsupervised domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3723–3732, 2018.

[17] Baochen Sun and Kate Saenko. Deep coral: Correlation alignment for deep domain adaptation. In *Proceedings of the European Conference on Computer Vision*, 2016.

[18] Eric Tzeng, Judy Hoffman, Kate Saenko, and Trevor Darrell. Adversarial discriminative domain adaptation. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, 2017.

[19] Rundi Wu, Xuelin Chen, Yixin Zhuang, and Baoquan Chen. Multimodal shape completion via conditional generative adversarial networks. In *The European Conference on Computer Vision (ECCV)*, August 2020.

[20] Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and Jianxiong Xiao. 3d shapenets: A deep representation for volumetric shapes. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1912–1920, 2015.

[21] Li Yi, Boqing Gong, and Thomas Funkhouser. Complete and label: A domain adaptation approach to semantic segmentation of lidar pointclouds, 2020.