DGSS: Domain Generalized Semantic Segmentation using Iterative Style Mining and Latent Representation Alignment

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Abstract

Semantic segmentation algorithms require access to well-annotated datasets captured under diverse illumination conditions to ensure consistent performance. However, poor visibility conditions at varying illumination conditions result in laborious and error-prone labeling. Alternatively, using synthetic samples to train segmentation algorithms has gained interest with the drawback of domain gap that results in suboptimal performance. While current state-of-the-art (SoTA) have proposed different mechanisms to bridge the domain gap, they still perform poorly in low illumination conditions with an average performance drop of ~ 10.7 mIOU. In this paper, we focus upon single source domain generalization to overcome the domain gap and propose a two-step framework wherein we first identify an adversarial style that maximizes the domain gap between stylized and source images. Subsequently, these stylized images are used to categorically align features such that features belonging to the same class are clustered together in latent space, irrespective of domain gap. Furthermore, to increase intra-class variance while training, we propose a style mixing mechanism wherein the same objects from different styles are mixed to construct a new training image. This framework allows us to achieve a domain generalized semantic segmentation algorithm with consistent performance without prior information of the target domain while relying on a single source. Based on extensive experiments, we match SoTA performance on SYNTHIA → Cityscapes, GTA V → Cityscapes while setting new SoTA on GTA V → Dark Zurich and GTA V → Night Driving benchmarks without retraining.

Introduction

Supervised learning of semantic segmentation (SS) algorithms requires access to large-scale and well-annotated datasets captured under diverse illumination and weather variations. However, collecting and labeling such large datasets is time-consuming and error-prone in adverse weather conditions. To reduce this data collection and annotation effort, synthetic datasets generated from game engines (GTAV (Richter et al. 2016), SYNTTHIA (Ros et al. 2016)) or from simulators (CARLA (Dosovitskiy et al. 2017)) are increasingly being used for training. However, domain gaps between synthetic and real images result in performance degradation when training solely on synthetic datasets while evaluating real datasets.

To alleviate this issue, unsupervised domain adaptation (UDA) or domain generalization (DG) mechanisms are utilized wherein DA minimizes the performance gap using an annotated source domain and unlabelled target domain. In contrast, domain generalization focuses on generalization across multiple unknown target domains using either single or multiple source domains. Despite being practically relevant, DG is particularly challenging since to ensure consistent performance across diverse distributions, knowledge of model bias is necessary to minimize prediction inaccuracies. On the contrary, domain adaptation leverages the availability of the target domain to reduce domain shift by relying either on adversarial learning (Vu et al. 2019a), feature alignment in pixel (Chen et al. 2019), (Choi, Kim, and Kim 2019), feature (Chang et al. 2019), (Hong et al. 2019), output (Tsai et al. 2019) space or self-training (Zhang et al. 2019), (Li, Yuan, and Vasconcelos 2019). While current methods demonstrate the feasibility of using a synthetic dataset for training SS algorithms via domain adaptation, the sensitivity of these algorithms in low illumination conditions or different domains highlights the drawback of these approaches, i.e., despite domain adaption, a trained SS model might not perform well in night conditions.

Figure 1: Results on day and night images from validation subset of Dark-Zurich Dataset.
In this paper, we propose a target free domain generalization mechanism built upon the notion that features representing the same object category across diverse domains should be similar in latent space irrespective of domain gap. While prior domain generalization works (Shyam, Yoon, and Kim 2021; Zhao et al. 2020; Qiao, Zhao, and Peng 2020) relied on leveraging multiple source domains to cover a large feature space, we propose that instead of gathering data from multiple synthetic sources, we could stylize the images using transformations that maximize the distance between the source and stylized image in latent space. This approach allows us to use the same ground truth label and ensures the underlying SS algorithm learns texture invariant structural details. However, using a fixed set of style information results in SS algorithms overfitting these representations and achieves sub-optimal performance. To avoid this, we integrate an iterative style mining approach to identify and use adversarial styles. Upon mining the adversarial styles, we utilize the ground truth labels to align the feature encodings categorically using contrastive learning wherein features belonging to the same category are clustered together and separated from other categories in latent space.

Inspired by different data augmentation techniques (Yun et al. 2019; Shyam et al. 2021; Ghiasi et al. 2021), to maximize intra-class feature distribution, we propose style mixing augmentation wherein a pool of stylized images we copy-paste different regions to generate an image mosaic such that features belonging to the same category would have different textures. Hence during the optimization process, for the categorical features to be clustered closely, their structural information would be emphasized, resulting in domain invariant characteristics. We demonstrate that the proposed mechanism allows for consistent performance irrespective of domain or illumination changes through extensive experiments. We summarize our contributions as:

- We propose an iterative style mining approach to identify adversarial styles to train a semantic segmentation network using a synthetic dataset.
- To ensure categorical feature alignment in latent space, we propose a contrastive learning mechanism to introduce push and pull forces to cluster similar features.
- For improving structural representation within features, we introduce a style mixing augmentation that results in features from the same category having different styles.
- Through extensive experiments on varying domains and illumination conditions, we demonstrate consistent performance using only a single source domain.

**Related Works**

**Domain Adaptation**: Current approaches for unsupervised domain adaptation (UDA) can be formulated either as adversarial learning, image translation or pseudo label based self-training. Adversarial learning-based approaches rely upon a discriminator to align the features either at global (Tsai et al. 2018) or local (Vu et al. 2019a) scale by tasking the discriminator to identify the source of the segmented image. Recently (Du et al. 2019; Luo et al. 2019; Wang et al. 2020) improved this approach by introducing an additional category aware distribution alignment. Another direction for UDA is aligning input images to match target images either using cyclic image translation mechanisms (Hoffman et al. 2018) or swapping portions of Fourier spectrum of source image with target image (Yang and Soatto 2020). Recently pseudo-label based self-training mechanisms have gained increasing interest on their ability to reach higher SoTA on account of generating pseudo labels for target domain and iteratively improving them while improving the performance of SS algorithm. Based on this notion, different algorithms leveraging entropy minimization (Chen, Xue, and Cai 2019; Saito et al. 2019; Wu et al. 2019a) was proposed that encourages the SS algorithm to improved predictions on unlabelled data. However, pseudo labels are prone to noise; thus, to reduce the effect of noise (Zhang et al. 2021) proposed estimation of pseudo categories and an online correction mechanism to improve the label quality.

**Illumination Invariance**: While UDA methods have shown promising results, their performance deteriorates significantly when evaluated in low illuminated conditions. Hence (Romera et al. 2019; Sun et al. 2019) proposed a CycleGAN (Zhu et al. 2017) based mechanism where cyclic day-to-night mapping is learnt. Subsequently, the training dataset is enlarged to contain images with varying illumination resulting in increased robustness at varying illumination conditions. Recently (Wu et al. 2021a) proposed a relight network to learn a mapping network between different illumination conditions such that low light images are enhanced to improve the performance of the semantic segmentation network. While these approaches result in consistent model performance under varying illumination conditions, a typical synthetic dataset is diverse enough to account for these conditions. Apart from these observations, we concur current SoTA UDA to be sensitive towards illumination variation based on our experiments.

**Image stylization for Domain Generalization**: From a practical perspective, it would be beneficial to have a framework that ensures consistent performance irrespective of domain gaps. With this motivation, (Muandet, Balduzzi, and Schölkopf 2013) proposed to learn domain invariant features using a kernel algorithm that minimizes the distributions between multiple distributions. Following this (Muandet, Balduzzi, and Schölkopf 2013) proposed to learn features that are domain invariant by using multiple source domains. Apart from prior approaches that aim to achieve domain generalization by learning domain invariant features, another way to achieve domain generalization is by way of data augmentation. Specifically (Jackson et al. 2019) proposed a style augmentation approach to preserve the structure of an image while modifying its texture using neural style transfer resulting in improved robustness of image classification and regression tasks towards domain shift. (Chattopadhyay, Balaji, and Hoffmann 2020) extends this approach by learning both domain variant and invariant features in a balanced manner such that the underlying model can perform well throughout. While domain generalization has gained interest for different tasks such as classification, we explore generation of multiple adversarial domains for semantic segmentation simply by the process of image styl-
Proposed Methodology

Our framework uses $N$ paired image samples $(x)$ with corresponding categorical labels $(y)$ from single source domain $(S = \{x_i, y_i\}_{i=1}^N)$ to train a semantic segmentation algorithm $F(\theta, C)$ with trainable parameters $\theta$ and maximum categories $C$, such that it retains performance in unseen domains by learning structural representations. For this we follow a two step process wherein we first identify styles that ensure maximum domain gap in feature space. Subsequently we apply these styles on training images and use categorical labels to align similar features in latent space. The complete pipeline is visually summarized in Fig. 2.

Iterative Style Mining: Prior domain generalization approaches relied upon data from multiple sources to ensure domain diversity using which domain invariant features are extracted for a given task. However in case of semantic segmentation, access to high quality diverse dataset is restricted. Alternatively, we propose to generate a large synthetic domain by identifying styles that maximize the feature distance between source and stylized images. As the styled features would be far apart from the source features while capturing the same scene, they can be treated as adversarial samples wherein the decoder of the SS algorithm would predict incorrect categories. Hence during training we determine different styles that maximize the distance between features of source and stylized features and use this style for training the underlying SS network without the need to generate a new label. To ensure the underlying SS algorithm learns the structural representation, we would vary the textural content of an image, hence to ensure a wide diversity of textural patterns during style mining process, we use Paintings (Johnson et al. 2008) and Textures (Cimpoi et al. 2014) as style translation sources.

For our implementation, we train a lightweight style translation algorithm $Styl(x_i, a)$ to obtain a style bank $(a)^A_i$ comprising 20 $(= A)$ styles from 10 paintings and 10 textures. Given the style bank, we stylize a mini-batch of 12 training images of size $512 \times 512$, and use the frozen encoder of the SS algorithm $(S_{enc}(\cdot))$ to generate feature embeddings corresponding to different stylized images along with source image $(x_i)$. We then compute the $L1$ distance between the stylized and source features to identify adversarial styles that are subsequently used to train the semantic segmentation network. During training it is expected for the underlying SS algorithm to extract features robust towards adversarial styles. Hence style mining is performed iteratively, throughout the training cycle to continuously obtain adversarial styles.

To ensure the style mining operation doesn’t create a bottleneck during training, we pre-train a Transformer ResNext Network, Pruned by a factor of 1.0 from (Mina 2018) for 25 randomly chosen textures and paintings with each model containing 63,459 parameters. Furthermore when inferencing these models we use fp16 to further increase processing speed.

Latent Representation Alignment: Irrespective of domain variations, features representing same categories should be clustered closely and separated from other clusters. The ability of the SS encoder to represent features resulting in such a segregation would unequivocally boost the segmentation quality. Hence to enforce such a segregation, we introduce latent representation alignment using prior categorical information. While earlier works (Toldo et al. 2020) have proposed a similar mechanism, they relied on prior source and target information resulting in performance retention only on known target domain whereas our method results in consistent performance across unknown domains. To enforce this segregation we utilize supervised constrastive learning (Khosla et al. 2020) (SupCon) wherein the image is first converted into feature matrix using the SS encoder $(S_{enc}(\cdot))$ from which pixel-level category based features $(S_{enc}(x) \rightarrow z)$ are extracted using corresponding label. Hence for an anchor pixel $(z_a)$ from pixel set $I$, based on category, features are divided into m-positive $(z^m_p)$ and n-negatives pixels.
Table 1: Performance Comparison with different SoTA domain adaptation algorithms for SYNTHIA → Cityscapes task. mIoU* denotes the mean IoU of 13 classes, excluding the classes marked by the asterisk.

| Method         | nod  | saskwalk | building | wall* | fence* | pole* | light | sign | vegetation | sky | person | rider | car | bus | motorcycle | haze | mIoU  | mIoU* |
|----------------|------|----------|----------|-------|--------|-------|-------|------|------------|-----|--------|-------|-----|-----|------------|------|-------|-------|
| Source Only    | 55.6 | 23.8     | 74.6     | 9.2   | 0.2    | 24.4  | 6.1   | 12.1 | 74.8        | 79.0| 55.3   | 19.1  | 39.6| 23.3| 13.7        | 74.8 | 79.0  | 55.3  |
| IAST           | 81.9 | 41.5     | 83.3     | 17.7  | 4.6    | 32.3  | 30.9  | 28.8 | 83.4        | 85.0| 65.5   | **30.8**| 86.5| 38.2| 52.7        | 49.8 | 57.0  |
| MetaCorrection | **92.6**| 52.7     | 81.3     | 8.9   | **2.4**| 28.1  | 13.0  | 7.3  | 83.5        | 85.0| 60.1   | 19.7  | 84.8| 37.2| 21.5        | 45.1 | 52.5  |
| PixMatch       | 42.5 | 54.6     | 79.8     | 4.7   | 0.0    | 24.1  | 22.8  | 17.8 | 79.4        | 76.5| 60.8   | 24.7  | 85.7| 33.5| 26.4        | 46.1 | 54.5  |
| ProDA          | 87.8 | 45.7     | 84.6     | 37.1  | 0.6    | 44.9  | 54.6  | 37.0 | 88.1        | 84.2| 74.2   | 24.3  | 88.2| 51.1| 40.5        | 55.5 | 62.0  |
| FDA            | 84.2 | 35.1     | 78.0     | 6.1   | 0.4    | 27.0  | 8.5   | 22.1 | 77.2        | 79.6| 55.5   | 19.9  | 74.8| 24.9| 40.7        | 40.5 | 48.0  |
| DGSS           | 90.8 | 50.0     | **84.6** | 24.8  | 1.9    | 38.4  | 29.7  | 36.3 | 86.0        | **87.9**| 67.5 | 30.7| 47.3        | 30.2| 54.0  | 52.3  |

While we ensure clustering of similar features to ensure they are far apart in feature space, we utilize cosine similarity to enforce perpendicularity between different features such that distance between features of different classes is maximum. Hence for each unique category cluster we compute the centroid after L1 normalization of features and subsequently use centroids \((c_j \in [1, C])\) of different categories to compute cosine similarity with each feature vector following,

\[
L_{\cosine} = \sum_{i=1}^{C} \sum_{j=1}^{m+n} \frac{c_j \cdot z_i}{\| c_j \|_2 \cdot \| z_i \|_2} \tag{2}
\]

This formulation allows in ensuring high distance between different category aware features and category centroids. The combination of supervised contrastive learning and cosine similarity allows in extracting features that exhibit the characteristic wherein same category features are close and far away from different category features.

**Style Mixing**: While we use image stylization as an alternative for multiple annotated sources that is necessary to ensure performance generalization. The diversity of objects present within the training batch could be small due to class imbalance. To overcome this propose style mixing augmentation that performs cut-mix (Yun et al. 2019) and copy-paste (Ghiasi et al. 2021) operations. Specifically while cut-mix operation focuses on extracting regions from an image and pasting onto another, copy-paste performs instance aware superimposition. Thus while cut-mix operation acts as a strong regularizer by creating inconsistent textural variations within the image, copy-paste mechanism results in images wherein different instances of same categorical features have different textural properties. Hence using these two augmentations jointly would ensure strong regularization effect while boosting the presence of structural features within the latent representation. We provide qualitative results of style mixing in supplementary.

**Complete Training Objective**: While our approach is generalizable to any semantic segmentation architecture, for our analysis following prior works we utilize DeepLabv2 architecture with ResNet-101 and VGG-16 as backbones. We implement the proposed framework in PyTorch and initialize the underlying SS encoder with ImageNet (Deng et al. 2009) and train the framework on system with a single Titan-V GPU (12GB) and 32GB RAM. We optimize the framework using Adam (Kingma and Ba 2014) with an initial learning rate of 0.0001 and batch size of 1 with GTA-V input resized to 1280 x 720 owing to GPU memory constraints. Furthermore for each source sample we perform style mixing once for epoch and utilize the stylized image with input image, resulting in an effective batch size of 2. We additionally use augmentations such as random flipping and color jittering as augmentations to avoid over fitting and train the models for 80k iterations following the loss objective,

\[
L = \lambda_1 \cdot L_{\cosine} + \lambda_2 \cdot L_{SupCon} \tag{3}
\]

here \(\lambda_1\) and \(\lambda_2\) are weight balances for loss functions which are set to 1 following ablation studies.

**Experiments**

**Datasets and Evaluation Metrics**: In order to extensively examine proposed framework, we utilize standard synthetic datasets such as GTA-V (Richter et al. 2016) and SYNTHIA (Ros et al. 2016) that act as source domains. Subsequently we use Cityscapes (Cordts et al. 2016), Dark-Zurich (Sakaridis, Dai, and Van Gool 2020a) and Night-Driving (Dai and Van Gool 2018) as target domains for evaluating the following scenarios SYNTHIA → Cityscapes, GTA → Cityscapes, GTAV → Dark Zurich and GTAV → Night Driving. For convenience we summarize the dataset properties in Tab.3 and elaborate the evaluation scenarios as,

- Consistent with prior works we use the validation subset of the Cityscapes dataset for evaluating GTA → Cityscapes and SYNTHIA → Cityscapes scenarios.
- To evaluate performance on night conditions, we retrain the SoTA algorithms using night subset of Dark-Zurich dataset and evaluate the performance on night conditions i.e. GTA → Dark Zurich.
- For examining domain generalization performance of SoTA algorithms we use Night Driving dataset i.e. GTA → Night Driving.

Since there lacks prior works focusing on achieving domain invariant semantic segmentation performance, we evaluate the performance of proposed framework with SoTA domain adaptation algorithms with ResNet-101 (He et al. 2015).
From performance results we can summarize that our proposed algorithm improves performance of baseline by 17.8 mIoU and 23.4 mIoU for GTAV → Cityscapes and SYNTHIA → Cityscapes scenarios respectively, consistently improving the classification accuracy for all categories without any prior information to target image or labels. Despite our approach relying solely on source information we achieve competitive performance with respect to SoTA (ProDA) while surpassing it on certain categories, demonstrating that access to target information is not a necessary requirement for performing domain adaptation. Rather we demonstrate that adversarial style mining and subsequent image stylization is sufficient to generate a diverse range of training samples that can be used for achieving domain generalization.

**Known Target but different Illumination** : Majority of prior works while evaluating performance on known target domain overlook the effect of illumination on segmentation performance. Hence we additionally evaluate performance under varying illumination conditions and thus utilize Dark-Zurich dataset that captures images of a scene at different illumination conditions i.e. day, twilight and night while surpassing it on certain categories, demonstrating that adversarial style mining and subsequent image stylization is sufficient to generate a diverse range of training samples that can be used for achieving domain generalization.

Table 3: Summary of different datasets used in this paper.

| Dataset      | GTAV | SYNTHIA | Cityscapes | Dark-Zurich | Night-Driving |
|--------------|------|---------|------------|-------------|---------------|
| # Classes    | 19   | 16      | 19         | 19          | 19            |
| # Total Samples | 24966 | 9400   | 6000       | 8377        | 50            |
| # Eval Samples | -    | -      | 500        | 50          | 50            |
| Resolution   | 1914 × 1052 | 1280 × 760 | 2048 × 1024 | 1920 × 1080 | 1920 × 1080 |

Table 2: Performance Comparison with different SoTA domain adaptation algorithms for GTAV → Cityscapes scenario.

![Figure 3: Qualitative Results on Cityscapes Dataset following GTAV → Cityscapes scenario.](image)
ful demonstration of robustness by proposed framework, we examine the effect of replacing iterative style mining with other approaches specifically (1) random sampled (RS) and (2) adversarial (ADV) methods. We investigate the performance of baseline algorithm that uses both feature representation alignment and iterative style mining. We further study the effect of different augmentation techniques and their combination on performance without any prior information about target domain. However due to different backbone a direct comparison of these algorithms would not be fair, hence we simply include performance of these algorithms to provide quantitative representation of SoTA on Dark-Zurich dataset. From Tab. 3 we can conclude that SoTA UDA algorithms are able to generalize better, their performance in blind condition where target information is unavailable. We thus use models trained for Cityscapes → Dark-Zurich scenario and evaluate their performance on Night Driving dataset alongside the proposed framework and summarize the quantitative and qualitative results in Tab. 5 and Fig. 5 respectively. While SoTA algorithms are able to generalize better, their performance is still lower, than observed when following the traditional scenarios of GTA V → Cityscapes and SYNTHIA → Cityscapes. We believe if the known target dataset contains diverse illumination conditions, it might alleviate the poor performance observed in low illumination conditions. Nevertheless, such an approach would indeed increase the burden of collecting and diversifying the target domain dataset.

Table 4: Performance Comparison with different SoTA domain adaptation algorithms for Cityscapes → Dark-Zurich scenario.

![Figure 4: Qualitative Results on Dark-Zurich Dataset following Cityscapes → Dark-Zurich scenario.](image)

**Ablation Studies** : We first examine the effect of different augmentation techniques and their combination on performance of baseline algorithm that uses both feature representation alignment and iterative style mining. We further examine the effect of replacing iterative style mining with other approaches specifically (1) random sampled (RS)
Table 5: Performance Comparison with different SoTA domain adaptation algorithms for Cityscapes → Dark Zurich evaluated on Night Driving.

| Method        | Source Only | ADVENT | FDA | DACS | DANNet | ProDA | DGSS |
|---------------|-------------|--------|-----|------|--------|-------|------|
| mIoU          | 59.0        | 21.8   | 53.0| 13.3 | 0.0    | 22.5  | 20.2 |
| mIoU          | 64.1        | 3.8    | 51.2| 2.4  | 0.1    | 11.2  | 50.5 |
| mIoU          | 52.0        | 12.6   | 76.6| 3.3  | 0.5    | 15.3  | 60.8 |
| mIoU          | 73.4        | 23.0   | 61.8| 10.6 | 0.0    | 23.5  | 56.7 |
| mIoU          | 89.7        | 57.5   | 84.5| 21.0 | 0.0    | 35.8  | 61.9 |
| mIoU          | 67.8        | 13.6   | 60.7| 6.9  | 0.2    | 17.6  | 63.1 |
| mIoU          | 86.5        | 60.2   | 86.4| 25.0 | 0.0    | 47.7  | 72.0 |

Table 6: Ablation Studies for Different Mechanisms

| Cut-Mix | Copy-Paste | \( \lambda_1 \) | \( \lambda_2 \) | FDA | RS | Baseline |
|---------|------------|-----------------|-----------------|-----|----|---------|
| ✓       | ✓          | 1.0             | 0.0             | 39.2| 41.1| 42.4    |
| ✓       | ✓          | 1.0             | 0.0             | 40.8| 47.6| 48.1    |
| ✓       | ✓          | 1.0             | 0.0             | 41.4| 48.8| 48.9    |
| ✓       | ✓          | 1.0             | 0.0             | 42.8| 49.7| 50.0    |
| ✓       | ✓          | 1.0             | 1.0             | 46.9| 49.9| 53.6    |

Figure 5: Qualitative Results on Night-Driving Dataset following Cityscapes → Dark-Zurich scenario.

Conclusion

This paper demonstrates that domain generalization for semantic segmentation could be achieved without any information about the target domain by simply identifying styles and textures that maximize the domain gap with respect to the source. Apart from generating diverse training distribution, we also perform latent representation alignment wherein categorical features are clustered together irrespective of the domain gap. Doing so ensures that the semantic segmentation algorithm learns structural details for making robust predictions. To examine the domain generalization performance, we conducted quantitative and qualitative experiments with SoTA UDA algorithms and achieved comparable performance to SoTA, however, the performance consistency was observed even for scenarios where SoTA UDA performed poorly, such as low illumination conditions.
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