GANs Distillation for One-shot Semantic Part Segmentation

Nontawat Tritrong* Pitchaporn Rewatbowornwong* Supasorn Suwajanakorn
Vidyasirimedhi Institute of Science and Technology
Rayong, Thailand
{nontawat.t_s19, pitchaporn.r_s18, supasorn.s}@vistec.ac.th

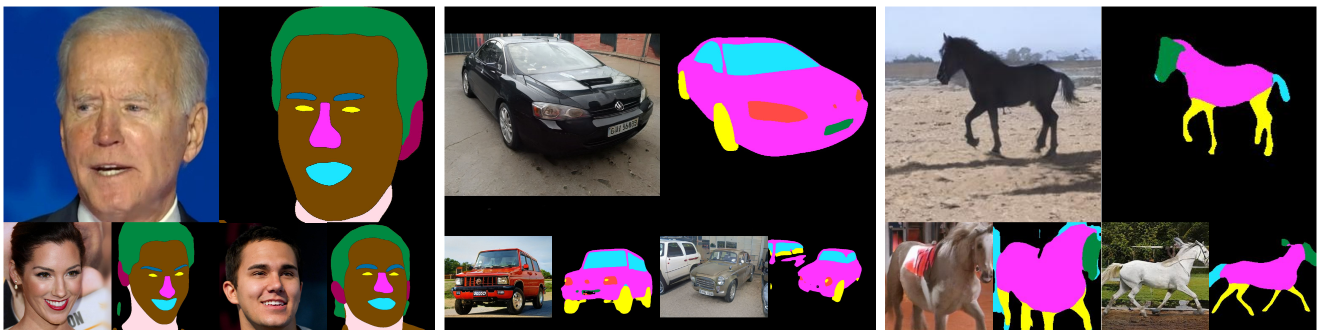

Figure 1: One-shot segmentation results. In each task, our segmentation network is given only one example of part labels.

Abstract

One main challenge of semantic part segmentation lies in its requirement for expensive pixel-wise annotations. Recent unsupervised and semi-supervised approaches either offer little control over object part assignment or still require many labels for other object classes to enable few-shot segmentation for a new class. In this work we propose a simple yet effective approach based on GANs for semantic part segmentation that requires as few as a single label example along with an unlabeled dataset. Our key idea is to leverage the knowledge from a trained GAN, traditionally only used for image synthesis, by using the information in the generator's activations as pixel-wise feature representation. Our novel use of GANs for unsupervised representation learning yields surprisingly good results that are comparable to those from supervised baselines trained with significantly more labels.

1. Introduction

After seeing what an elephant trunk looks like for the first time, a young child can identify this conspicuous part for the whole herd. This key capability in humans is still a fundamental challenge in computer vision. That is, how can a machine learn to identify an object or its parts by seeing only one or few examples? A kid does, however, have access to prior visual information learned constantly throughout the years, and he or she could quickly learn to identify an ear perhaps by utilizing the experience of seeing many faces before. In this paper, we tackle a problem inspired by this scenario. Given a large photo collection of human faces, or any other object classes, our goal is to identify the pixels corresponding to each semantic part for unseen face images given *very few* images with part annotations.

This problem setup is different from the typical definition of few-shot learning, which describes a problem where a learning algorithm trained with many classes needs to classify or operate on new classes with only few supervised examples of those new classes. In contrast, our novel few-shot setup involves a single object class with few annotated examples and no other training data from any other classes. Many methods are proposed in this area of few-shot learning, and the general idea is to apply prior knowledge learned externally to the few-shot task. Examples include meta learning [39] and prototype representation [31, 49] which extract information from annotations of non-target classes or image-level annotations to be used as prior knowledge. However, most of these approaches still learn from some supervised task that requires expensive labels or part annotations. In this work, we introduce a new direction that uses a generative model, specifically a generative adversar-

*Authors contributed equally to this work.

ial network (GAN) [19], to learn this prior knowledge from zero labels and apply it to semantic segmentation.

GANs have been highly successful in modeling the data distribution and generating realistic images [25, 26, 4]. We believe that GANs need to learn meaningful structural information of objects in order to synthesize them correctly, and the generative computations required to synthesize different parts of object could provide useful discriminative information for other tasks [2, 36]. Our main contribution is a method that leverages a trained GAN to extract meaningful pixel-wise representations from images. These representations can then be used directly for semantic part segmentation. Our experiments show that GANs are incredibly effective for learning such a representation and can achieve surprisingly good segmentation results with only one example label (see Figure 1). To our knowledge, this is the first time such high-quality results are achieved on one-shot part segmentation.

While our few-shot segmentation with representation from GANs yields remarkable results, there are challenges to overcome to build a practical system. First, a time-consuming latent optimization process is required to extract this representation for an unseen test image, and second, the test image has to lie on the image distribution learned by GAN to obtain a good representation. To overcome these issues, we additionally propose a simple framework that uses a GAN and our segmentation network to automatically generate a large annotated dataset with auxiliary label confidence. Using this dataset, an end-to-end segmentation network can be trained to solve segmentation from raw images without the latent optimization, leading to faster and more efficient inference. We call this process auto-shot segmentation. Our experiment shows that this auto-shot segmentation network produces comparable results to the few-shot network that is used to generate the dataset; and by performing geometric data augmentation on the generated dataset, the auto-shot network is able to part-segment multiple objects with different sizes and orientations—a real-world scenario infeasible for the few-shot network.

Apart from solving segmentation, we believe this novel pixel-wise representation distillation of GANs underlies a new direction for using unsupervised generative models for feature learning or as an "upstream" transfer learning task. We demonstrate its promising utility on few-shot part segmentation, a problem where annotations are significantly more expensive to obtain than image classification, and propose a framework that utilizes the GANs' ability to generate a dataset, leading to a solution that solves practical real-world segmentation.

2. Related Work

Representation Learning The goal of representation learning is to capture the underlying information from raw data that is useful and more convenient to process for downstream tasks. Many approaches learn these representations from solving one task and employ them to help improve the performance on another task [12, 40, 18, 38, 10, 23]. Recent studies have demonstrated that representations learned through a self-supervised task can boost the performance of supervised tasks such as classification and segmentation. Examples of these self-supervision tasks include spatial relative position prediction [11, 33], image colorization [28], and image transformation classification [25, 15]. In contrast, our work explores a representation learned from a generative task, i.e., image synthesis, and extracts feature vectors at the pixel-level that is more effective for segmentation problems.

Generative Models Deep generative models have shown promising results in modeling image distribution, thus enabling synthesis of realistic images. There are several classes of visual generative models which include autoregressive models [34, 47], autoencoders based on encoder-decoder architectures such as VAE and its variants [27, 21, 6, 46], and generative adversarial networks (GANs) [19]. Currently, GANs are best in class in image synthesis and have been applied to many other tasks such as image completion [35] and image-to-image translation [24, 56]. State-of-the-art GANs, such as StyleGAN2[26] and BigGAN[4], can generate extremely realistic images at high resolution. Our work employs GANs for representation learning, and we provide a study that shows the effectiveness of GANs over alternative models.

Motivated by the impressive results from GANs, numerous studies attempt to understand and interpret the internal representations of GANs. GANs dissection [3] applies an external segmentation model to find the relationship between feature maps and output objects, which also allows adding and removing objects in the output image. Suzuki et al. [43] show that interchanging activations between images can result in interchanging of objects in the output image. Edo et al. [9] use clustering to find distinctive groups of feature maps and allow spatially localized part editing. Tsutsui et al. [45] improve one-shot image recognition by combining images synthesized by GANs with the original training images. [13] uses representations learned from BigGAN and achieves state-of-the-art performance on unsupervised representation learning on ImageNet.

Some other studies analyze GANs through manipulation of the latent code and attempt to make GANs' internal representations more interpretable. Chen et al.[7] use mutual information to force the network to store human-interpretable attributes in their latent code. Shu et al.[41] solve a similar problem via an additional encoder network, which allows users to have control over the generated results. AttGAN [20] exploits an external classifier network to enable attribute editing. In this paper, we leverage the insight that GANs internal representations are tightly coupled to the generated output and that they can hold useful semantic information.

Semantic Part Segmentation Unlike semantic segmentation, this problem aims to segment parts within an object as opposed to objects within a scene. This problem can be more challenging because two parts sometimes do not have a visible boundary between them, such as nose and face. Considerable progress has been made in semantic part segmentation [48, 50, 44, 32], but these techniques demand a vast amount of pixel-wise annotations.

To avoid using pixel-wise annotations, some approaches rely instead on other kinds of annotations that are cheaper to obtain, such as keypoints [16], body poses [52], or edge maps [54]. However, they are often inflexible and only work on some specific domains such as human bodies. Some other attempts forgo the annotations completely with self-supervised techniques. For example, [22] uses equivariance, geometric, and semantic consistency constraints to train a segmentation network, and [29, 51] exploit motion information from videos. One main drawback of these unsupervised methods is that there is little control over the partition of object parts which can lead to arbitrary segmentation. Unlike these approaches, our method allows complete control over the partition of object parts by requiring only few annotated examples.

Few-shot Semantic Segmentation Past research has attempted to solve segmentation with few annotations. A meta learning approach [39] first trains a segmentation network on an annotated dataset then fine-tunes the network parameters on one annotation of the target class. Prototypical methods [14, 31, 49] use a support set to learn a prototype vector for each object class. Both meta learning and prototypical methods construct two training branches where the support branch is trained on annotations of non-target classes or image-level annotations, and the query branch then takes an input image as well as the extracted feature to predict segmentation masks. Similarity guidance network [53] uses segmentation mask to mask off the background in support image, then using only features from object to guide the query branch to locate pixel with high similarity to the features from support branch. Some work [42, 5] segment objects in all video frames with only the first frame annotated. Nonetheless, these methods have not shown success in semantic part segmentation. Meta learning requires annotation masks of similar object classes, and hence learning part-specific prototypes is not viable. Leveraging the information from the support set is also difficult due to the lack of part-level annotations. In contrast, our representation extracted from GANs contains part-level information and can be learned without supervision.

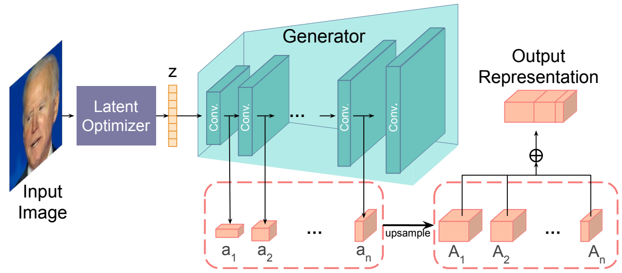

Figure 2: **Representation extraction** To extract a representation from an image, we embed the image into the latent space of GAN by optimizing for the latent z that reproduces the input image. z is then fed to the generator and we collect multiple activation maps $a_1, a_2, ..., a_n$ of dimensions $(h_1, w_1, c_1), ..., (h_n, w_n, c_n)$. Each of these maps is upsampled to A_i with dimension (h_n, w_n, c_i). The representation is a concatenation of all A_i along the channel dimension.

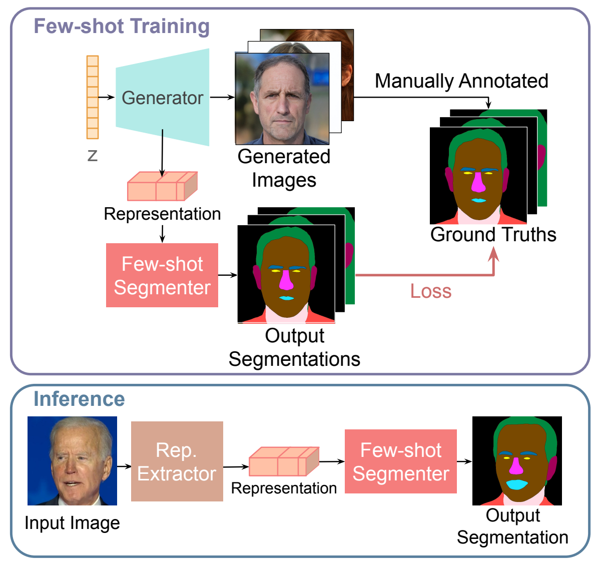

Figure 3: **Few-shot segmentation pipeline** For training, we use a trained GAN to generate a few images along with their representations by feeding random latent codes. Then, we manually annotate these images and train our few-shot segmenter to output segmentation maps that match our annotated masks. For inference, we extract a representation from a test image (Figure 2) then input it to the few-shot segmenter to obtain a segmentation map.

3. Approach

Our problem concerns semantic part segmentation with the following novel setup. Given an image dataset of a single object class, our goal is to segment an unseen object from the same class by learning from few images with part annotations. These part annotations are specified by bi-

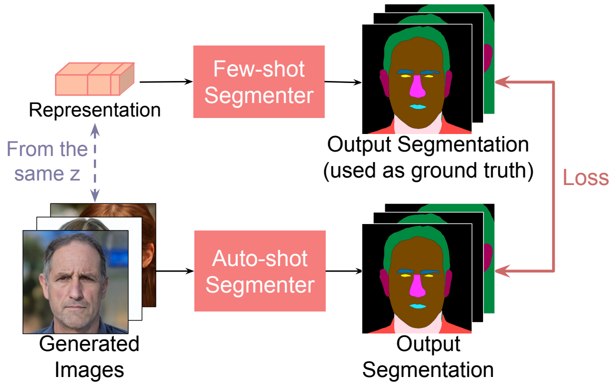

Figure 4: **Auto-shot segmentation pipeline** during training, the auto-shot segmenter uses generated images from GANs as input and segmentation masks predicted by the few-shot segmenter as output.

nary masks. Note that semantic part segmentation can also be considered as an n-way *per-pixel* classification problem where n is the number of parts.

This problem would become trivial if there exists a function f that maps each pixel value, which by itself lacks semantic meaning, to its own feature vector that contains discriminative information for part classification. We propose to derive such a function from a GAN trained to synthesize images of the target class. In the following sections, we will explain how GANs are utilized for this task, how to use the computed per-pixel features for segmentation, and a novel pipeline that involves a second network to perform segmentation without relying on GAN and its expensive mapping.

3.1. Representation Extraction from GANs

Using GANs as a mapping function is not straightforward simply because GANs take as input a random latent code, not the image pixels to be mapped. To understand our process, first consider a typical scenario where we generate an image by feeding a random latent code to a convolutional-based GAN. In this case, the synthesized output image is constructed by the generator through a series of spatial convolutions, and each output pixel is a result of a unique generative computation that can be traced back through each convolution layer down to the initial latent code.

Our key idea is to use these unique computational "paths" for feature representation. In general, the computational path for generating a pixel forms a directed acyclic graph with nodes representing the network parameters or input latent code involved in the computation of that pixel. However, in our work these nodes represent activation values, and we simply represent the path with a single sequence of activations from all layers within the generator that are spatially aligned with that pixel. As illustrated in Figure 2, we extract the activation map from every layer (or some subset of layers) of the generator and upsample each map to the size of the largest activation map. These activation maps are then concatenated in the channel dimension and together represent a feature map of size $H \times W \times C$ where C is the number of activation maps combined from all layers. This process maps each 3-dimensional RGB pixel to a $C-$dimensional feature vector.

Normally, this extraction process only works for images that are synthesized by the generator and cannot be used directly for real test images. However, given any test image, one can optimize for a latent code that generates that given test image with any gradient-based optimization or with more sophisticated schemes [26, 1, 17]. The resulting latent code then allows the feature map to be constructed in a similar manner.

3.2. Segmentation with Extracted Representation

To solve few-shot segmentation, we first train a GAN on images of our target class and generate k random images by feeding it random latent codes. Then, we compute feature maps and manually annotate object parts for these k images. The k feature maps and annotations together form our supervised training pairs which can be used to train a neural network such as a multilayer perceptron or a convolutional network (see Figure 3). To segment a test image, we compute a pixel-wise feature map for the test image using the aforementioned latent code optimization and feed it to our trained network.

3.3. Auto-shot Segmentation Network

Computing pixel-wise feature vectors using a GAN does have a number of restrictions. First, the test image needs to lie close to the image distribution modeled by the GAN; otherwise, the latent optimization may not work well to reproduce the test image, leading to a poor feature vector. This constrain can be severely restricting for classes like human face because it requires the test image to be aligned and centered similarly to the images used to train the GAN. Second, relying on a GAN to generate feature vectors through a latent optimization process is time-consuming and also expensive if the GAN's model is large.

To overcome these limitations, we use our trained GAN to synthesize a large set of images and predict segmentation maps for those images using our network to form paired training data. To retain all the probability information from our network's prediction process, each pixel in our segmentation maps is represented by a set of logit values of all part labels rather than a single part ID. That is, we do not apply softmax and argmax to produce the segmentation maps. With this training data, we train another network, e.g. a UNet [37], to solve the segmentation from raw images without relying on GAN or its feature mapping (see Figure 4).

We call this process auto-shot segmentation. Additionally, we apply data augmentation that allows detection of objects at different scales and orientations. Interestingly, we demonstrate how this simple approach can successfully segment multiple object instances at the same time with good quality in our experiments and supplementary video.

4. Implementation

Our training pipeline starts by training a GAN on a dataset of the target class. Then, we use the trained GAN to generate a few images along with their pixel-wise representations (Section 3.1) and manually annotate these images with the desired part segmentation. Finally, we train a few-shot segmentation network that takes as input the pixel-wise representation to predict an output segmentation. For the auto-shot segmentation, we use the same GAN to generate a large dataset of images and use our trained few-shot network to predict segmentation maps for those images. These generated images and their corresponding segmentation maps are then used to train the auto-shot segmentation network.

4.1. Generative Adversarial Network

We use StyleGAN2 [26] for our pipeline. StyleGAN2 has 9 pairs of convolution layers with activation outputs of sizes: 4^2, 8^2, 16^2, 32^2, 64^2, 128^2, 256^2, 512^2, and 1024^2. For feature extraction, we use all pairs except the last which generates the output image. We also use StyleGAN2's projection method proposed in their paper to embed an image into the latent space (latent code optimization explained in Section 3.1).

4.2. Few-shot Segmentation Network

The few-shot network takes the C-channel pixel-wise representation as input and output a segmentation map. We explore 2 different architectures: fully convolutional networks (CNN) and multilayer perceptrons (MLP).

CNN: We first use a linear embedding layer (1x1 convolution) to reduce the input dimension from 5,056 to 128, followed by 8 convolutional layers with kernel size of 3 and dilation rates of 2, 4, 8, 1, 2, 4, 8, and 1. The dimensions of the output channels are: 64 for the first 6 layers, 32, and the number of classes. All layers except the output layer use leaky ReLU activation functions.

MLP: We use a 2-layer MLP with 2,000 and 200 hidden nodes for the first and second layers. All layers except the output layer use ReLU activation functions.

Both MLP and CNN were trained for 1,000 epochs with a cross-entropy loss and a weight decay of 0.001 using Adam optimizer. Our initial learning rate is 0.001 with a decay factor of 10 every 50 epochs.

Table 1: IOU scores on few-shot human face segmentation.

Segmentation Network	shots	3-class	10-class
CNN	1	71.7	77.9
	5	82.1	83.9
	10	**83.5**	**85.2**
MLP	1	75.3	74.1
	5	77.8	79.6
	10	77.2	77.2

Table 2: Per-class IOU scores on 3-class human face segmentation.

	weighted IOU	Eyes	Mouth	Nose
1-shot	71.7	57.8	71.1	76.0
5-shot	82.1	73.6	84.0	82.1
10-shot	83.5	75.9	85.3	82.7

4.3. Auto-shot Segmentation Network

This network is trained with GAN's generated images and their corresponding segmentation maps from the few-shot network. We adopt a UNet architecture described in our supplementary. Additionally, we perform the following data augmentation on this training set 1) random horizontal flips, 2) random scales between 0.5 and 2, 3) random rotations between -10 and 10 degree, 4) random vertical and horizontal translations between 0% and 50% of the image size. This network is trained for 300 epochs using Adam optimizer with an initial learning rate of 0.001 and a decay factor of 0.1 when the validation score does not decrease within 20 epochs.

5. Experiments

We perform the following experiments in this section: 1) we evaluate the performance of our few-shot and auto-shot segmenters on 3 object classes and compare them to baselines, 2) we study whether the choice of layers used for feature extraction affects the segmentation performance, 3) we test whether our method can segment parts that have arbitrary or unusual shapes that do not correspond to any semantic parts. Additionally in our supplementary, 4) we show segmentation results on videos, 5) we explore and evaluate features learned from other generative models, such as VAE, or from other supervised and self-supervised learning methods and compare against our features learned from GANs, 5) we evaluate alternative structures of the few-shot segmentation network.

5.1. Semantic Part Segmentation

We evaluate segmentation performance of the few-shot and auto-shot segmenters on 3 object classes: human face, and car.

Table 3: IOU scores of our 10-shot vs auto-shot segmenters on 10-class face segmentation. The auto-shot segmenter is trained with a dataset generated by the 10-shot segmenter. Both techniques have similar performance which demonstrates the effectiveness of the dataset generation process.

Network	weighted IOU	Eyes	Mouth	Nose	BG/face	Clothes	Hair	Eyebrows	Ears	Neck	BG
Few-shot segmenter	85.2	74.0	84.6	82.9	90.0	23.6	79.2	63.1	27.0	73.6	84.2
Auto-shot segmenter	84.5	75.4	86.5	84.6	90.0	15.5	84.0	68.2	37.3	72.8	84.7

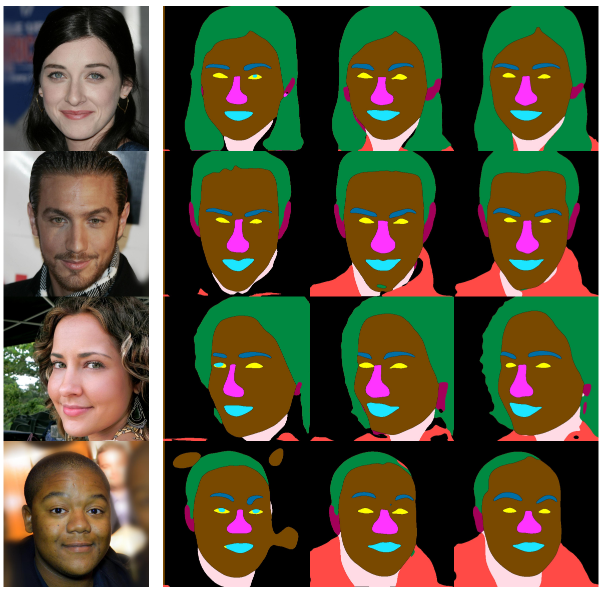

Figure 5: Few-shot part segmentation results.

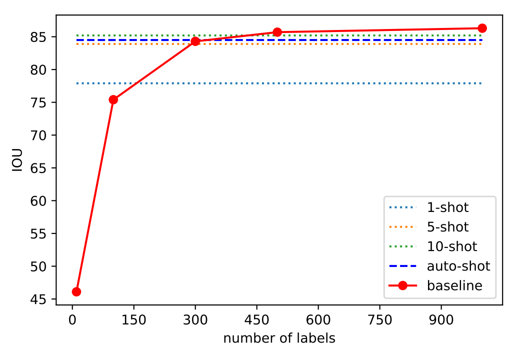

Figure 6: 10-class face segmentation results of supervised baseline and the number of segmentation labels used. Our few-shot segmentation results are shown in dot line for comparison. Supervised baseline consumes over 100 annotations to surpass our 1-shot segmenter, and around 500 annotation to reach same-level of IOU on our 10-shot segmenter.

Datasets: We use face images and annotated segmentation masks from CelebAMask-HQ [30] to train the few-shot face segmenter. For horse and car, we use pretrained StyleGAN2 models to generate images up to 10 that are then manually annotated. For the dataset used to train the auto-shot segmenter, we use 5,000 images generated from each GAN trained on each object class and the predicted annotations from the few-shot segmenter. The results are evaluated on CelebAMask-HQ for faces and PASCAL-Part dataset[8] for cars and horses.

Evaluation metric: We use intersect-over-union (IOU) to evaluate individual object parts and report weighted IOU scores that weight each part by the number of pixels of that part over all pixels in the image.

Table 4: IOU scores on PASCAL-Parts car segmentation.

Model	Body	Plate	Light	Wheel	Window	BG	Average
CNN[44]	73.4	41.7	42.2	66.3	61	67.4	58.7
CNN+CRF[44]	75.4	35.8	36.1	64.3	61.8	68.7	57
Ours	75.5	17.8	29.3	57.2	62.4	70.7	52.2
OMPS[55]	86.3	50.5	55.1	75.5	65.2	-	66.5
Ours w/o bg	76.4	17.5	29.3	52.5	64.1	-	47.9

Table 5: IOU scores on PASCAL-Parts horse segmentation. "-" indicates no available result.

Model	Head	Neck	Torso	Neck+Torso	Legs	Tail	BG
Shape+Appearance[48]	47.2	-	-	66.7	38.2	-	-
CNN+CRF[44]	55.0	34.2	52.4	-	46.8	37.2	76.0
Ours	50.1	-	-	70.5	49.6	19.9	81.6

Table 6: Average IOU scores on PASCAL-Parts horse segmentation.

Model	RefineNet[16]	Pose-Guided[32]	Ours
Horse IOU	36.9	60.2	53.1

Table 7: Comparison of 1-shot segmentation performance with representation from different layers of GANs.

Layers	Resolution	weighted mean IOU
A	$4^2 - 8^2$	59.6
B	$16^2 - 32^2$	**79.1**
C	$64^2 - 512^2$	69.0
A-B	$4^2 - 32^2$	75.2
B-C	$16^2 - 512^2$	75.0
A-B-C (all)	$4^2 - 512^2$	**77.9**

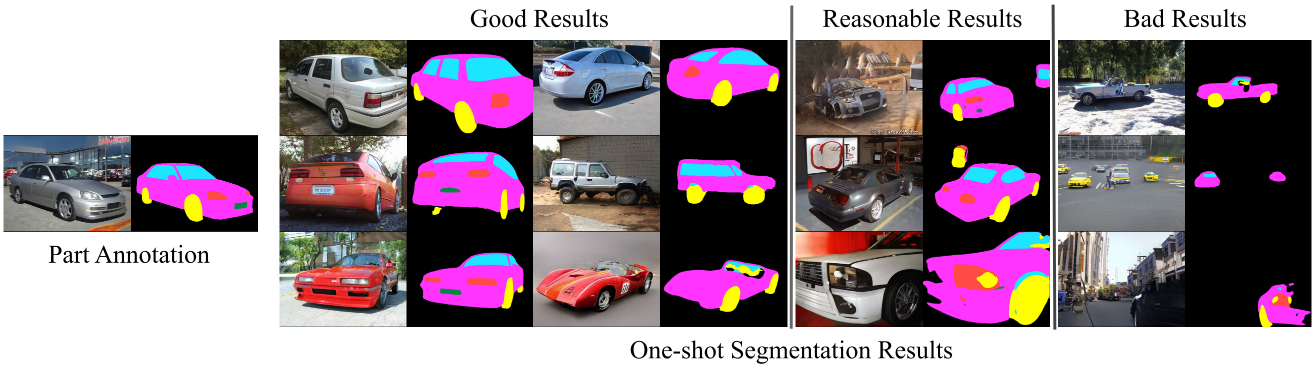

Figure 7: One-shot car part segmentation results. The segmentation network can segment car images from varied points of view even though it only sees car from one perspective during training. However, there are some failure cases when the cars are too close, too far, or when GANs generates unrealistic cars.

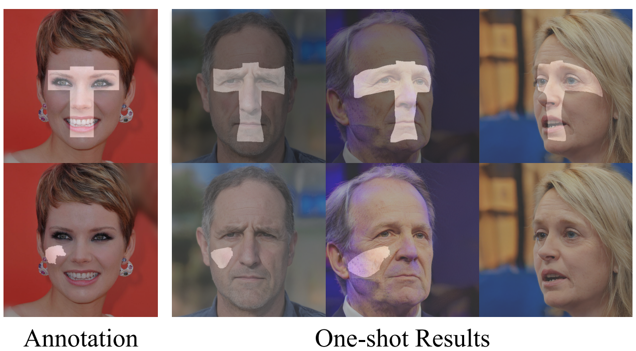

Figure 8: Given segmentation masks with arbitrary, meaningless shapes that have no clear boundary, our approach can infer the same regions across different face images and can even recognize it when the regions are stretched or out of view.

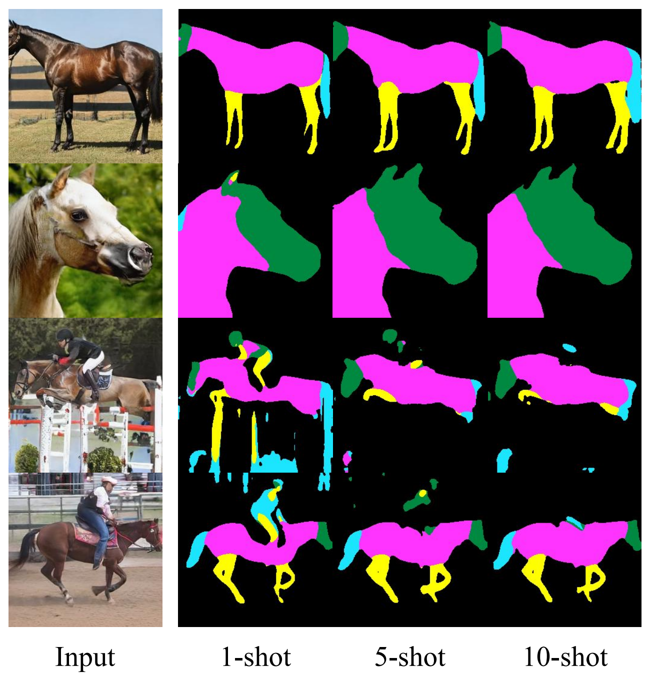

Figure 9: Results on few-shot horse part segmentation. Compared to cars and faces with good 1-shot results, horses need more labels. 1-shot horse segmentation often mistakes the rider as a part of horse.

5.1.1 Human Face Part Segmentation

We perform experiments with 12 combinations of settings that vary 1) the architecture of the few-shot segmenter (CNN or MLP), 2) the number of part classes (3 or 10), and 3) the number of examples with part annotations (1-shot, 5-shot, 10-shot). The results are shown in Table 1.

Table 3 shows IOU scores of the few-shot segmenter and auto-shot segmenter on 10-class face segmentation. Surprisingly, the auto-shot segmenter achieves slightly higher IOUs in all part classes except for clothes, even though it relies only on the dataset generated by the few-shot segmenter. Note that the few-shot network also performs poorly on clothes relative to other parts, which could be due to the large variation in clothing. The auto-shot segmenter can also segment unaligned images at various scales due to the data augmentation during training. Figure 6 shows a 10-class segmentation comparison between our few-shot and auto-shot segmenters and a supervised baseline which uses the same architecture as the auto-shot segmenter and is trained on ground-truth masks from CelebAMask-HQ with varying numbers of labels. Our few-shot segmenter trained with a single label produces a comparable IOU score to the supervised baseline trained with about 150 labels. And with 10 labels, both of our segmenters match the baseline performance with 500 labels. Qualitative and quantitative results

Figure 10: Some examples of auto-shot segmentation trained with datasets generated by 10-shot segmenters.

for the CNN-based few-shot network are shown in Figure 5 and Table 2.

5.1.2 Car Part Segmentation

Unlike well-aligned face images in CelebA-HQ, car images in PASCAL-Part have larger variations in pose and appearance. Despite this challenge, our one-shot segmenter produces good segmentation results and can identify wheels, windows, and the license plate shown in Figure 7. We compare our method to DeepCNN-DenseCRF [44] and the Ordinal Multitask Part Segmentation[55] on the car class in PASCAL-Part. Details on the experiment setup can be found in our supplementary. Table 4 shows our results using the auto-shot segmenter trained on a 10-shot dataset (dataset generated from our few-shot segmenter with 10 labels), which compares favorably to the fully supervised baselines. Note that we compare to [55] by excluding the background class similarly to how their scores were reported.

5.1.3 Horse Part Segmentation

Horse segmentation is more challenging than the other two because horses are non-rigid and can appear in many poses such as standing or jumping. Also, the boundaries between legs and body are not clearly visible. Our one-shot segmenter has lower performance compared to those of faces and cars; however, the result improves significantly with a few more annotations as shown in Figure 9. In Table 5, we compare our auto-shot segmentation (also learned from dataset by 10-shot segmenter) IOU scores on each class to Shape+Appearance [48] and CNN+CRF [44]. Table 6 shows the overall IOU scores of our auto-shot segmenter, RefineNet[16], and Pose-Guided Knowledge Transfer [32]. The score of RefineNet is taken from [32]. Our method surpasses RefineNet, and our IOU is slightly lower than Pose-Guided Knowledge Transfer [32] which is a fully-supervised method trained with over 300 annotated images and additional annotated keypoints. Experimental details can be found in our supplementary.

5.2. Effects of GAN's Layer Selection

A study on style mixing from StyleGAN [25] suggests that information in earlier layers of a GAN's generator controls the higher-level appearance of the output image whereas late layers control the subtle detail. In this experiment, we explore whether choosing different subsets of layers from the generator can affect the performance. Similarly to the study in StyleGAN, we roughly split the layers into 3 groups: (A) the coarse style (from resolution $4^2 - 8^2$), (B) the middle style ($16^2 - 32^2$), and (C) the fine style ($64^2 - 1024^2$). Then, we test our one-shot segmenter by feeding different combinations of these groups shown in Table 7. The result shows that the representation from group B yields the highest IOU with a slight increase from using all layers, and group A performs the worst. This suggests that the middle layers that control the variation and appearance of facial features are more useful for our face segmentation network when only few examples are available.

5.3. Arbitrary Segmentation

We have shown that features from GANs are effective for part segmentation when those parts, so far, correspond to some natural semantic regions such as eyes and mouth. In this experiment, we test whether features from GANs are restricted to those parts and whether our method can generalize to any arbitrary segmented shapes. We manually create random shaped annotations and use them to train our few-shot network. Figure 8 shows that our method can still handle semantic-less parts and produce consistent segmentation across people and head poses.

6. Conclusion

We present a simple and powerful approach to semantic part segmentation. Our novelty lies in the unconventional use of pixel-wise representation extracted from generative processes of GANs. Our approach demonstrates surprising and promising performance that allows part segmentation given very few annotations as low as one label example. We also propose a framework that utilizes GANs to generate a dataset that allows another segmentation network to generalize better to real-world scenarios with multiple objects of varying sizes. Our experiments show that our few-shot approach produces comparable results to a fully-supervised baseline that requires 10-100× more label examples. We believe this novel use of GANs underlies a new class of unsupervised representation learning that is applicable to many other tasks.

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