Unsupervised Cross-Modality Domain Adaptation of ConvNets for Biomedical Image Segmentations with Adversarial Loss基于无监督跨模态域自适应ConvNets的对抗损失医学图像分割

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Abstract

Convolutional networks (ConvNets) have achieved great successes in various challenging vision tasks. However, the performance of ConvNets would degrade when encountering the domain shift. 卷积网络(ConvNets)在各种具有挑战性的视觉任务中取得了巨大的成功。然而，当遇到域迁移时，ConvNets的性能会下降。The domain adaptation is more significant while challenging in the field of biomedical image analysis, where cross-modality data have largely different distributions. 域自适应在生物医学图像分析领域具有更重要的意义，同时也具有挑战性，因为在生物医学图像分析领域，跨模态数据分布具有很大的差异。Given that annotating the medical data is especially expensive, the supervised transfer learning approaches are not quite optimal. 考虑到标注医疗数据特别昂贵，有监督的迁移学习方法并不是很理想。In this paper, we propose an unsupervised domain adaptation framework with adversarial learning for cross-modality biomedical image segmentations. 本文提出了一种基于对抗性学习的无监督领域自适应框架，用于跨模态生物医学图像分割。Specifically, our model is based on a dilated fully convolutional network for pixel-wise prediction. Moreover, we build a plug-and-play domain adaptation module (DAM) to map the target input to features which are aligned with source domain feature space.具体地说，我们的模型是基于扩展的全卷积网络进行像素预测的。此外，我们还构建了即插即用域适配模块(DAM)，将目标输入映射到与源域特征空间对齐的特征。 A domain critic module (DCM) is set up for discriminating the feature space of both domains. We optimize the DAM and DCM via an adversarial loss without using any target domain label.建立了领域批评模块(DCM)，用于区分两个领域的特征空间。我们通过对抗性损失来优化DAM和DCM，而不使用任何目标域标签。 Our proposed method is validated by adapting a ConvNet trained with MRI images to unpaired CT data for cardiac structures segmentations, and achieved very promising results.我们提出的方法通过把用MRI图像训练的模型应用到未配对的CT数据上进行验证，并取得了非常令人振奋的成果。

# Introduction

Deep convolutional networks (ConvNets) have demonstrated great achievements in recent years, achieving state-of-the-art or even human-level performance on various computer vision challenging problems, such as image recognition, semantic segmentation as well as biomedical image diagnosis [He *et al.*, 2016; Esteva *et al.*, 2017]. 近年来，深层卷积网络(ConvNets)取得了巨大的成就，在图像识别、语义分割以及生物医学图像诊断等各种计算机视觉挑战问题上取得了最先进的甚至是人类水平的性能[He等人，2016；Esteva等人，2017]。Typically, the deep networks are trained and tested on datasets where all the samples are drawn from the same probability distribution. However, it has been observed that established models would under-perform when tested on samples from a related but not identical new target domain [Shimodaira, 2000].通常，深度网络是在所有样本都来自相同概率分布的数据集上进行训练和测试的。然而，已经观察到，当对来自相关但不相同的新目标领域的样本进行测试时，已建立的模型将表现不佳[Shimodaira，2000]。

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Cardiac

MRI

Cardiac CT



*AA*

*LV*

*-*

*blood*

Intensity

V

oxels

MRI

CT

Source Domain

Target Domain



MS

-

COCO



VOC2007



VOC2007



MS

-

COCO

*LV*

*-*

*myo*

Figure 1: Illustration of severe domain shift existing in crossmodality biomedical images. The appearances of the anatomical structures (AA: ascending aorta, LV-blood: left ventricle blood cavity, LV-myo: left ventricle myocardium) would vary significantly on MRI and CT images. Compared with natural image datasets (see bottom examples), domain adaptation for cross-modality medical images encounter more challenges.说明跨模态生物医学图像中存在严重的结构域漂移。解剖结构(AA：升主动脉，LV-blood：左心室腔，LV-MYO：左心室心肌)在MRI和CT图像上的表现有显著差异。与自然图像数据集(见下图)相比，跨模态医学图像的领域自适应面临更多挑战。

The existence of *domain shift* is common in real-life applications [Gretton *et al.*, 2009; Torralba and Efros, 2011]. The semantic class labels are usually shared between domains, whereas the distributions of data are different. 域迁移的存在在现实应用中很常见[Gretton等人，2009；Torralba和Efros，2011]。语义类标签通常在域之间共享，而数据的分布是不同的。In the field of biomedical image analysis, this issue is even more obvious. Unlike natural images which are generally taken by optical devices, medical radiological images are acquired by different imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). 在生物医学图像分析领域，这个问题更加明显。与通常由光学设备拍摄的自然图像不同，医学放射图像是通过不同的成像方式获取的，例如计算机断层扫描(CT)和磁共振成像(MRI)。Data distributions of these modalities mismatch significantly, due to their different principles of imaging physics. 由于成像物理原理的不同，这些模态的数据分布明显不匹配。The appearance of anatomical structures are distinct across radiology modalities, with obviously different intensity histograms. 解剖结构的外观在不同的放射学模式中是不同的，具有明显不同的强度直方图。In Fig. 1, we illustrate the severe domain shift between MRI/CT data. In comparison with examples from natural datasets, domain adaptation for cross-modality medical data is more challenging.在图1中，我们展示了MRI/CT数据之间的严重域移。与自然数据集的例子相比，跨模态医学数据的领域自适应更具挑战性。

To tackle this issue, domain adaptation methods have been studied to generalize the learned models [Patel *et al.*, 2015]. The domain of labeled training data is termed as *source domain*, and the test dataset is called *target domain*.为了解决这个问题，已经研究了领域适应方法来推广学习到的模型[Patel等人，2015年]。带标签的训练数据域被称为源域，测试数据集被称为目标域。 A straightforward solution is transfer learning, i.e., fine-tuning the models learned on source domain with extra labeled data from the target domain [Pan and Yang, 2010]. 一个简单的解决方案是迁移学习，即用来自目标域的额外标记数据微调在源域学习的模型[Pan and Yang，2010]。However, the annotation is prohibitively time-consuming and expensive, especially for those biomedical datasets. 然而，标注非常耗时且昂贵，特别是对于那些生物医学数据集。Alternatively, the unsupervised domain adaptation methods are more feasible, given that these scenarios transfer knowledge across domains without using additional target domain labels.或者，考虑到这些场景在不使用额外的目标域标签的情况下跨域传输知识，无监督的域自适应方法更可行。 Advanced studies in this direction have taken advantage of adversarial training to implicitly learn the feature mapping between domains, and achieved remarkable success in natural datasets [Ganin *et al.*, 2016; Tzeng *et al.*, 2017].这一方向的前沿研究中利用对抗训练来隐式学习两个域之间的特征映射，并在自然数据集上取得了显著的成功。

Currently, for biomedical images, how to effectively generalize ConvNets across domains has not yet been fully studied. 目前，对于生物医学图像，如何有效地跨域泛化ConvNet还没有得到充分的研究。A representative work is [Kamnitsas *et al.*, 2017] which conducted unsupervised domain adaptation for brain lesion segmentation and achieved promising results. 一个代表性的工作是[Kamnitsas等人，2017]，他们对脑病变进行了无监督的域自适应，并取得了令人振奋的结果。However, their source and target domains are relatively close, given that both are MRI datasets although acquired with different scanners. Adapting ConvNets between cross-modality radiology images with a huge domain shift is more compelling for clinical practice, but has not been explored yet.然而，它们的源域和目标域相对较近，因为两者都是MRI数据集，尽管是用不同的扫描仪获取的。在具有巨大域移的跨模态放射学图像之间采用ConvNets在临床实践中更具吸引力，但尚未被探索。

In this paper, we propose a novel cross-modality domain adaptation framework for medical image segmentations with unsupervised adversarial learning. 本文提出了一种新的基于无监督对抗性学习的跨模态域自适应医学图像分割框架。To transfer the established ConvNet from source domain (MRI) to target domain (CT) images, we design a plug-and-play domain adaptation module (DAM) which implicitly maps the target input data to the feature space of source domain. 为了将建立的ConvNet从源域(MRI)图像传输到目标域(CT)图像，我们设计了一个即插即用域适配模块(DAM)，它将目标输入数据隐式映射到源域的特征空间。Furthermore, we construct a discriminator which is also a ConvNet termed as domain critic module (DCM) to differentiate the feature distributions of two domains. 此外，我们还构造了一个鉴别器，它也是一个称为域批评模块(DCM)的ConvNet，用于区分两个域的特征分布。Adversarial loss is derived to train the entire domain adaptation framework in an unsupervised manner, by placing the DAM and DCM into a minimax two-player game. Our main contributions are:通过将DAM和DCM放入极小极大两人博弈中，导出了对抗性损失，以无监督的方式训练整个领域适应框架。我们的主要贡献是：

* We pioneer cross-modality domain adaptation for medical image segmentation using deep ConvNets. A flexible plug-and-play framework is designed to transfer a MRI segmenter to CT data via feature-level mapping.我们首创了基于深度卷积网络的跨模态域自适应医学图像分割方法。设计了一种灵活的即插即用框架，通过特征级映射将MRI分割器转移到CT数据。
* We optimize our framework with unpaired MRI/CT images via adversarial learning in an unsupervised manner, eliminating the cost of labeling extra medical datasets.我们通过对抗性学习以无监督的方式使用未配对的MRI/CT图像优化我们的框架，消除了标记额外医学数据集的成本。
* Extensive experiments with promising results on cardiac segmentation application have validated the feasibility of radiology cross-modality domain adaptation, as well as the effectiveness of our approach towards this task.大量实验在心脏分割应用上取得了令人振奋的结果，验证了放射学跨模态领域自适应的可行性，以及我们针对这一任务的方法的有效性。

# Related Work

Domain adaptation aims to confront the performance degradation caused by any distribution change occurred after learning a classifier. 领域自适应的目的是对抗在学习分类器后分布发生变化导致的性能下降。For deep learning models, this situation also applies, and a trend of studies have been conducted to map the target input to the original source domain or its feature space. 对于深度学习模型，这种情况也适用，并且已经有学习趋势将目标输入映射到原始源域或其特征空间。In this section, we first present related works of unsupervised domain adaptation that achieved promising results on natural image datasets. Next, we review the recent studies on domain adaptation for medical image segmentations using ConvNets.在这一部分中，我们首先介绍了无监督领域自适应的相关工作，这些工作在自然图像数据集上取得了令人振奋的结果。接下来，我们回顾了基于ConvNets的医学图像分割领域自适应的研究现状。

Most prior studies on unsupervised domain adaptation focused on aligning the distributions between domains in feature space, by minimizing measures of distance between features extracted from the source and target domains. 以往的无监督领域自适应研究大多集中于通过最小化从源域和目标域提取的特征之间的距离来对齐特征空间中域之间的分布。For example, the Maximum Mean Discrepancy (MMD) was minimized together with a task-specific loss to learn the domaininvariant and semantic-meaningful features in [Tzeng *et al.*, 2014]. 例如，最大均值差异(MMD)（再生核希波尔特空间最大均值差）与任务特定的损失一起被最小化，以学习领域不变和语义有意义的特征[Tzeng等人，2014]。The correlations of layer activations between the domains were aligned in the study of [Sun and Saenko, 2016]. Based on this, [Wang *et al.*, 2017] further extended the work and minimized domain difference based on both the first and second order information between source and target domains. 在Sun和Saenko的研究中，域之间的层激活关系是一致的[Sun和Saenko，2016]。在此基础上，[Wang等人，2017]进一步扩展了工作，并基于源域和目标域之间的一阶（均值向量差范数）和二阶信息（协方差矩阵差范数）最小化了域差异。Alternatively, with the emergence of generative adversarial network (GAN) [Goodfellow *et al.*, 2014] and its powerful extensions [Radford *et al.*, 2015; Arjovsky *et al.*, 2017], the mapping between domains were implicitly learned via the adversarial loss. 或者，随着生成性对抗网络(GAN)的出现[古德费罗等人，2014]及其强大的扩展[Radford等人，2015；Arjovsky等人，2017]，域之间的映射是通过对抗性损失隐式学习的。The [Ganin *et al.*, 2016] proposed to extract domain-invariant features by sharing weights between two ConvNet classifiers. [Ganin等人，2016]提出通过在两个ConvNet分类器之间共享权重来提取领域不变特征。Later, the [Tzeng *et al.*, 2017] introduced a more flexible adversarial learning method with untied weight sharing, which helps effective learning in the presence of larger domain shifts. 后来，[Tzeng等人，2017]引入了一种更灵活的解开权重共享的对抗性学习方法，有助于在存在较大域转移的情况下进行有效学习。Another GAN based direction of solution is to learn a transformation in the pixel space [Bousmalis *et al.*, 2017], adapting the source-domain images to appear as if drawn from the target domain.另一个基于GaN的解决方向是学习像素空间中的变换[Bousmalis等人，2017]，使源域图像看起来好像是从目标域绘制的。

In the field of medical image analysis using deep learning, domain adaptation is also an important topic to generalize learned models across data acquired from different imaging protocols. 在使用深度学习的医学图像分析领域，领域自适应也是在不同成像协议获取的数据中推广学习模型的一个重要课题。Transfer learning with network fine-tuning strategies has been experimentally studied by [Ghafoorian *et al.*, 2017] on the brain lesion segmentation application. Although the amount was small, annotations from target domain were still required in their scenario. 带有网络微调策略的迁移学习已经由[Ghafoorian等人，2017年]在脑病变分割应用上进行了实验研究。虽然数量很小，但在他们的场景中仍然需要来自目标域的标注。The latest study on medical data that is closely related to our work is [Kamnitsas *et al.*, 2017], which performed unsupervised domain adaptation for brain lesion segmentation. 与我们的工作密切相关的最新医学数据研究是[Kamnitsas等人，2017年]，它对大脑病变分割执行了无监督的域适应。Their ConvNets learned domaininvariant features on images, with an adversarial loss serving as the supervision for feature extraction. 他们的ConvNets学习图像上的领域不变特征，对抗性损失作为特征提取的监督。The results were inspiring and demonstrated the efficacy of adversarial loss for unsupervised domain adaptation on medical datasets. 研究结果鼓舞人心，证明了在医学数据集上进行非监督领域自适应的对抗性损失的有效性。However, their source and target domains are relatively close, because both were MRI datasets. Although acquired with different scanners and imaging protocols, the images were from the same modality and the domain shift was not dramatic. 然而，它们的源域和目标域相对较近，因为它们都是MRI数据集。尽管使用不同的扫描仪和成像协议获取图像，但图像来自相同的模式，并且域的变化并不显著。In contrast, our problem setting, i.e., adapting a ConvNet trained on MRI data to CT images, is novel but more adventurous and challenging, since our domain shift is more severe.相比之下，我们的问题设置，即采用基于MRI数据和CT图像训练的ConvNet，是新颖的，但更具冒险性和挑战性，因为我们的域转换更严重。

# Methods

The Fig. 2 presents our proposed framework for unsupervised cross-modality domain adaptation in biomedical image segmentation. 图2展示了我们提出的在生物医学图像分割中无监督跨模态领域自适应的框架。Based on a standard ConvNet segmenter, we construct a plug-and-play domain adaptation module (DAM) and a domain critic module (DCM) to form adversarial learning. 基于一个标准的ConvNet分割器，我们构造了一个即插即用的领域适配模块(DAM)和一个领域鉴别模块(DCM)来形成对抗性学习。Details of network architecture, adaptation method, adversarial loss and training strategies are elaborated in this section.本部分详细阐述了网络结构、自适应方法、对抗性损失和训练策略。

## ConvNet Segmenter Architecture ConvNet分割器体系结构

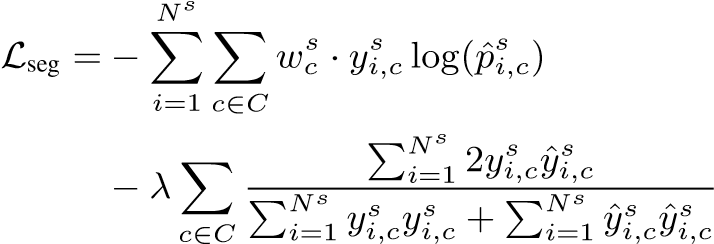
With the labeled dataset of *Ns* samples from source domain, denoted by, we conduct supervised learning to establish a mapping from the input image to the label space *Y s*.对于来自源域的Ns 个样本的标记数据集，表示为，我们进行监督学习以建立从输入图像到标签空间Y s的映射。In our setting, the *xsi* represents the

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| --- |
| Figure 2: Overview of our proposed plug-and-play framework for cross-modality domain adaptation. The DAM and DCM are optimized via adversarial learning. During inference, the domain router is used for routing feature maps of different domains.我们提出的用于跨模态域适应的即插即用框架的概述。 DAM 和 DCM 通过对抗性学习进行优化。 在推理过程中，域路由器用于路由不同域的特征图。 |

sample (pixel or patch) of medical images andis the category of anatomical structures. 在我们的设置中， xsi 表示图像的样本(像素或斑点)，表示解剖结构的类别。For the ease of denotation, we omit the index *i* in the following, and directly use *xs* and *ys* to represent the samples and labels from the source domain.为了便于表示，我们省略了下面的索引i，直接使用 *xs* 和*ys*来表示源域中的样本和标签。

The mapping *Ms* from input to the label space is implicitly learned in the form of a segmentation ConvNet. 从输入到标签空间的映射*Ms*以分割ConvNet的形式隐式学习。The backbone of our segmenter is the residual network for pixelwise prediction of biomedical images. 我们的分割器的主干是用于生物医学图像的像素化预测的残差网络。

We employ the dilated residual blocks [Yu *et al.*, 2017] to extract representative features from a large receptive field while preserving the spatial acuity of feature maps. 我们使用膨胀的残差块[Y u等人，2017]从大的感受野中提取代表性特征，同时保持特征图的空间灵敏度。More specifically, the image is firstly input to a Conv layer, then forwarded to 3 residual modules (termed as RM, each consisting of 2 stacked residual blocks) and downsampled by a factor of 8. 更具体地说，图像首先被输入到卷积层，然后被转发到3个残差模块(称为RM，每个残差模块由2个堆叠的残差块组成)，并被下采样8倍。Next, another three RMs and one dilated RM are stacked to form a deep network. To enlarge receptive field for extracting global semantic features, 4 dilated convolutional layers are used in RM7 with a dilation factor of 2. 接下来，堆叠另外三个RM和一个膨胀的RM以形成深网络。为了放大用于提取全局语义特征的接收领域，在RM7中使用4个膨胀 的卷积层，其膨胀因子为2。For dense predictions in our segmentation task, we conduct upsamling at layer *Conv10*, which is followed by 5×5 convolutions to smooth out the feature maps. Finally, a softmax layer is used for probability predictions of the pixels.对于我们的分割任务中的密集预测，我们在图层CONV10中进行了上采样，然后是5×5卷积来平滑特征映射。最后，Softmax层用于像素的概率预测。

The segmentation ConvNet using labeled data from source domain is optimized by minimizing the hybrid loss Lseg composed of the multi-class cross-entropy loss and the Dice coefficient loss [Milletari *et al.*, 2016]. 通过最小化由多级交叉熵损失和Dice系数损失组成的混合损失Lseg 来优化使用来自源域的标记数据的分割ConvNet[Milletari等，2016]。Formally, we denote *yi,cs* for binary label regarding class *c*∈*C* in sample *xsi*, its probability prediction is, and the label prediction is, the source domain segmenter loss function is as follows:正式的，在样本 *xsi* 中，我们用*yi,cs* 表示关于类*c*∈*C* 的二元标签，它的概率预测是，预测标签是，源域分割器损失函数如下

(1)

*,*

## where the first term is the cross-entropy loss for pixel-wise classification, with *wcs* being a weighting factor to cope with the issue of class imbalance.其中，第一项是用于像素级分类的交叉熵损失， *wcs*是处理类别不平衡的一个权重因子。 The second term is the Dice loss for multiple cardiac structures, which is commonly employed in biomedical image segmentation problems. 第二项是多个心脏结构的Dice损失，这通常用于生物医学图像分割问题。We combine the two complementary loss functions to tackle the challenging heart segmentation task. In practice, we also tried to use only one type of loss, but the performance was not quite high.我们结合了两个互补的损失函数来处理具有挑战性的心脏分割任务。在实践中，我们也试图只使用一种类型的损失，但性能并不太高。

## Plug-and-Play Domain Adaptation Module即插即用域适应模块

When the ConvNet is learned on the source domain, our goal is to generalize it to a target domain. In transfer learning, the last several layers of the network are usually fine-tuned for a new task with new label space. 当ConvNet在源域上学习时，我们的目标是将其推广到目标域。在迁移学习中，网络的最后几层通常会针对具有新标签空间的新任务进行微调。The supporting assumption is that early layers in the network extract low-level features (such as edge filters and color blobs) which are common for vision tasks. 支持的假设是网络中的早期层提取视觉任务中常见的低级特征(如边缘过滤器和彩色斑点)。Those upper layers are more task-specific and learn high-level features for the classifier [Zeiler and Fergus, 2014; Yosinski *et al.*, 2014].这些更上层是具体的任务和学习分类器的高级特征[泽勒和弗格斯，2014；Yosinski等人，2014]。 In this case, labeled data from target domain are required to supervise the learning process. Differently, we use unlabeled data from the target domain, given that labeling dataset is time-consuming and expensive. 在这种情况下，需要来自目标域的标记数据来监督学习过程。不同的是，我们使用来自目标域的未标记数据，因为标记数据集既耗时又昂贵。This is critical in clinical practice where radiologists are willing to perform image computing on cross-modality data with as less extra annotation cost as possible. Hence, we propose to adapt the ConvNet with unsupervised learning.这在临床实践中至关重要，因为放射科医生愿意以尽可能少的额外标注成本对跨模态数据执行图像计算。因此，我们建议将ConvNet与无监督学习相结合。

In our segmenter, the source domain mapping *Ms* is layerwise feature extractors composing stacked transformations of , with the *l* denoting the network layer index. Formally, the predictions of labels are obtained by:在我们的分割器中，源域映射*Ms*是构成堆叠变换的层级特征提取器，l表示网络层索引。在形式上，标签的预测通过以下方式获得:

*.* (2)

For domain adaptation, the label space of source and target domains are identical, i.e., we segment the same anatomical structures from medical MRI/CT data.对于域自适应，源域和目标域的标记空间是相同的，即我们从医学MRI/CT数据中分割相同的解剖结构。 Our hypothesis is that the distribution changes between the cross-modality domains are primarily low-level characteristics (e.g., gray-scale values) rather than high-level (e.g., geometric structures).我们的假设是，跨模态域之间的分布变化主要是低级特征(例如灰度值)，而不是高级特征(例如几何结构)。 The higher layers (such as) are closely in correlation with the class labels which can be shared across different domains. 较高层(如)与可跨不同域共享的类标签密切相关。In this regard, we propose to reuse the feature extractors learned in higher layers of the ConvNet, whereas the earlier layers are updated to conduct distribution mappings in feature space for our unsupervised domain adaptation.在这方面，我们建议重用在ConvNet的更高层中学习的特征提取器，而更早的层被更新以在特征空间中进行分布映射，用于我们的无监督域自适应。

For the input from target domain *xt*, we propose a domain adaptation module denoted by M that maps *xt* to the feature space of the source domain.对于来自目标域*xt*,的输入，我们提出了一个用M表示的域自适应模块，它将*xt* 映射到源域的特征空间。 We denote the adaptation depth by *d*, i.e., the layers earlier than and including *ld* are replaced by DAM when processing the target domain images. 我们用d来表示适应深度，即在处理目标域图像时，用DAM来替换早于和包括*ld*的层。In the meanwhile, the source model’s upper layers are frozen during domain adaptation learning and reused for target inference. Formally, the predictions for target domain is as:同时，源模型的上层在域自适应学习过程中被冻结，并被重新用于目标推理。从形式上看，目标域的预测如下:



whererepresents the DAM which is also a stacked ConvNet. 其中代表DAM，它也是一个堆叠的ConvNet。总的来说，我们形成了一个灵活的即插即用域适配框架。Overall, we form a flexible plug-and-play domain adaptation framework. During the test inference, the DAM directly replaces the early d layers of the model trained on source domain. 总的来说，我们形成了一个灵活的即插即用域适配框架。在测试推理期间，DAM直接替换在源域上训练的模型的早期d层。The images of target domain are processed and mapped to deep learning feature space of source domain via the DAM. 目标域的图像通过深度学习算法处理并映射到源域的深度学习特征空间。These adapted features are robust to the cross-modality domain shift, and can be mapped to the label space using those high-level layers established on source domain. 这些适应的特征对于跨模态域变换是鲁棒的，并且可以使用在源域上建立的那些高级层映射到标签空间。In practice, the ConvNet configuration of the DAM is identical to. We initialize the DAM with trained source domain model and fine-tune the parameters in an unsupervised manner with adversarial loss.实际上，DAM的ConvNet配置与相同。我们用训练好的源域模型初始化DAM，并以无监督的方式微调参数，避免不利损失。

## Learning with Adversarial Loss使用对抗损失学习

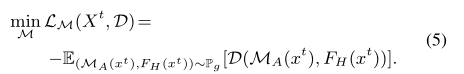
We propose to train our domain adaptation framework with adversarial loss via unsupervised learning. The spirit of adversarial training roots in GAN, where a generator model and a discriminator model form a minimax two-player game. 我们建议通过无监督学习来训练我们的领域适应框架。对抗训练的精神源于GAN，在GAN中，一个生成器模型和一个鉴别器模型形成了一个极小极大两人游戏。The generator learns to capture the real data distribution; and the discriminator estimates the probability that a sample comes from the real training data rather than the generated data.生成器学习捕捉真实的数据分布；鉴别器估计样本来自真实训练数据而不是生成数据的概率。 These two models are alternatively optimized and compete with each other, until the generator can produce real-like samples that the discriminator fails to differentiate. 这两个模型交替优化并相互竞争，直到生成器可以产生鉴别器无法区分的真实样本。For our problem, we train the DAM, aiming that the ConvNet can generate source-like feature maps from target input. Hence, the ConvNet is equivalent to a generator from GAN’s perspective.对于我们的问题，我们训练DAM，目标是ConvNet可以从目标输入中生成类似源的特征映射。因此，从GAN的角度来看，ConvNet相当于一个生成器。

Considering that accurate segmentations come from highlevel semantic features, which in turn rely on fine-patterns extracted by early layers, we propose to align multiple levels of feature maps between source and target domains (see Fig. 2). 考虑到精确的分割来自高级语义特征，而高级语义特征又依赖于由早期层提取的精细模式，我们建议在源域和目标域之间对齐多级特征映射(见图2)。In practice, we select several layers from the frozen higher layers, and refer their corresponding feature maps as the set of *FH*(·) where *H*={*k,...,q*} being the set of selected layer indices. 实际上，我们从冻结的较高层中选择几个层，并将它们对应的特征映射称为 *FH*(·)的集合，其中H={k，...q}是所选层索引的集合。Similarly, we denote the selected feature maps of DAM by M*A*(·) with the *A* being the selected layer set. 同样的，我们用M*A*(·)来表示DAM的所选特征映射，A是所选的层集。In this way, the feature space of target domain is (M*A*(*xt*)*,FH*(*xt*)) and the (*MAs*(*xs*)*,FH*(*xs*)) is their counterpart for source domain. 这样，目标域的特征空间是(M*A*(*xt*)*,FH*(*xt*)) ，而对应(*MAs*(*xs*)*,FH*(*xs*))是源域的。Given the distribution of (M*A*(*xt*)*,FH*(*xt*))∼P*g*, and that of (*MAs*(*xs*)*,FH*(*xs*)) ∼ P*s*, the distance between these two domain distributions which needs to be minimized is represented as *W*(P*s,*P*g*). 给定(M*A*(*xt*)*,FH*(*xt*))∼P*g*的分布，以及(*MAs*(*xs*)*,FH*(*xs*)) ∼ P*s*的分布，这两个域分布之间需要最小化的距离表示为*W*(P*s,*P*g*)。For stabilized training, we employ the Wassertein distance [Arjovsky *et al.*, 2017] between the two distributions as follows:对于稳定训练，我们采用两个分布之间的Wassertein距离[Arjovsky等人，2017]，如下所示:

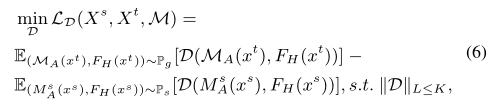
*,* (4)

where  represents the set of all joint distributions *γ*(x*,*y) whose marginals are respectively and .其中，表示所有联合分布 *γ*(x*,*y)的集合，其边缘分别为和。

In adversarial learning, the DAM is pitted against an adversary: a discriminative model that implicitly estimates the *W*(P*s,*P*g*). 在对抗式学习中，DAM面对的是一个对手：一个鉴别模型隐含估计*W*(P*s,*P*g*)We refer our discriminator as domain critic module and denote it by D. Specifically, our constructed DCM consists of several stacked residual blocks, as illustrated in Fig. 2. 我们称我们的鉴别器为域批评模块，并用D表示。具体地说，我们构造的DCM由几个堆叠的残差块组成，如图2所示。In each block, the number of feature maps is doubled until it reaches 512, while their sizes are decreased. We concatenate the multiple levels of feature maps as input to the DCM. This discriminator would differentiate the complicated feature space between the source and target domains.在每个块中，特征图的数量增加一倍，直到达到512个，同时其大小减小。我们将多个级别的特征图连接起来作为DCM的输入。该鉴别器将区分源域和目标域之间的复杂特征空间。 In this way, our domain adaptation approach not only removes source-specific patterns in the beginning but also disallows their recovery at higher layers [Kamnitsas *et al.*, 2017]. 通过这种方式，我们的域自适应方法不仅在开始时移除了特定于源的模式，而且还不允许在更高层恢复它们[Kamnitsas等人，2017]。In unsupervised learning, we jointly optimize the generator M (DAM) and the discriminator D (DCM) via adversarial loss. Specifically, with *Xt* being target set, the loss for learning the DAM is: 在无监督学习中，我们通过对抗损失联合优化生成器M (DAM)和鉴别器D (DCM)。具体来说，在设定 *Xt* 目标的情况下，学习DAM的损失为:



Furthermore, with the *Xs* representing the set of source images, the DCM is optimized via: 此外，使用*Xs* 代表源图像集，DCM通过以下方式进行优化:



where *K* is a constant that applies Lipschitz contraint to D.其中，K是一个常数，它将 Lipschitz约束应用于D。

During the alternative updating of M and D, the DCM outputs a more precise estimation of *W*(P*s,*P*g*) between distributions of the feature space from both domains. 在M和D的交替更新期间，DCM输出来自两个域的特征空间分布之间的*W*(P*s,*P*g*)的更精确的估计。The updated DAM is more effective to generate source-like feature maps for conducting cross-modality domain adaptation.更新后的DAM更有效地生成源样特征映射，以进行跨模态域自适应。

## Training Strategies训练策略

In our setting, the source domain is biomedical cardiac MRI images and the target domain is CT data. 在我们的设置中，源域是生物医学心脏MRI图像，目标域是CT数据。All the volumetric MRI and CT images were re-sampled to the voxel spacing of 1×1×1 mm3 and cropped into the size of 256×256×256 centering at the heart region. 将所有体积的磁共振和计算机断层扫描图像重新采样到1×1×1 mm3的体素间距，并以心脏区域为中心裁剪成256×256×256的大小。In preprocessing, we conducted intensity standardization for each domain, respectively. Augmentations of rotation, zooming and affine transformations were employed to combat over-fitting. 在预处理中，我们分别对每个域进行强度标准化。旋转、缩放和仿射变换的增强被用来对抗过度拟合。To leverage the spatial information existing in volumetric data, we sampled consecutive three slices along the coronal plane and input them to three channels. The label of the intermediate slice is utilized as the ground truth when training the 2D networks.为了充分利用体积数据中存在的空间信息，我们沿着冠状面对连续的三个切片进行采样，并将它们输入三个通道。当训练2D网络时，中间切片的标签被用作基本事实。

We first trained the segmenter on the source domain data in supervised manner with stochastic gradient descent. The Adam optimizer was employed with parameters as batch size of 5, learning rate of 1×10−3 and a stepped decay rate of 0.95 every 1500 iterations. 我们首先用随机梯度下降的监督方式对源域数据进行训练。亚当优化器的参数为批量5，学习率1×10−3，每1500次迭代的步进衰减率0.95。After that, we alternatively optimized the DAM and DCM with the adversarial loss for unsupervised domain adaptation. Following the heuristic rules of training WGAN [Arjovsky *et al.*, 2017], we updated the DAM every 20 times when updating the DCM. 遵循训练WGAN的启发式规则[Arjovsky等人，2017]，我们在更新DCM时每20次更新一次DAM。In adversarial learning, we utilized the RMSProp optimizer with a learning rate of 3× 10−4 and a stepped decay rate of 0.98 every 100 joint updates, with weight clipping for the discriminator being 0.03.在对抗性学习中，我们使用了RMSProp优化器，其学习率为3× 10−4，每100次联合更新的步进衰减率为0.98，鉴别器的权重剪裁为0.03。

# Experiment

## Dataset and Evaluation Metrics数据集和评估指标

We validated our proposed unsupervised cross-modality domain adaptation method for biomedical image segmentations on the public dataset of *MICCAI 2017 Multi-Modality Whole*

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| --- |
| (a) CT Image (b) CT Label (c) Seg-CT-STL (d) Seg-CT (e) Seg-CT-noDA (f) Seg-CT-UDA  Figure 3: Results of different methods for CT image segmentations. Each row presents one typical example, from left to right: (a) raw CT slices (b) ground truth labels (c) supervised transfer learning (d) ConvNets trained from scratch (e) directly applying MRI segmenter on CT data (f) our unsupervised cross-modality domain adaptation results. The structures of AA, LA-blood, LV-blood and LV-myo are indicated by yellow, red, green and blue colors, respectively (best viewed in color).CT 图像分割的不同方法的结果。 每一行从左到右展示一个典型示例：(a) 原始 CT 切片 (b) 真实标签 (c) 监督迁移学习 (d) 从头开始训练的 ConvNets (e) 在 CT 数据上直接应用 MRI 分割器 (f) 我们的无监督跨模态域适应结果。 AA、LA-blood、LV-blood 和 LV-myo 的结构分别用黄色、红色、绿色和蓝色表示（最好用彩色显示）。 |

*Heart Segmentation* [Zhuang and Shen, 2016]. 我们在MICCAI 2017多模态全心分割的公共数据集上验证了我们提出的无监督跨模态领域自适应生物医学图像分割方法。This dataset consists of unpaired 20 MRI and 20 CT images from 40 patients. The MRI and CT data were acquired in different clinical centers. 该数据集包括来自40名患者的20张未配对的MRI和20张CT图像。在不同的临床中心采集MRI和CT资料。The cardiac structures of the images were manually annotated by radiologists for both MRI and CT images. 这些图像的心脏结构由放射科医生为MRI和CT图像进行手动标注。Our ConvNet segmenter aimed to automatically segment four cardiac structures including the ascending aorta (AA), the left atrium blood cavity (LA-blood), the left ventricle blood cavity (LV-blood), and the myocardium of the left ventricle (LVmyo). 我们的ConvNet心脏分割仪的目标是自动分割四个心脏结构，包括升主动脉(AA)、左心房血腔(LA-HOLD)、左心室血腔(L-V-HOLD)和左心室心肌(L-V-MYO)。For each modality, we randomly split the dataset into training (16 subjects) and testing (4 subjects) sets, which were fixed throughout all experiments.对于每种模式，我们将数据集随机分成训练集(16名受试者)和测试组(4名受试者)，这两组数据在所有实验中都是固定的。

For evaluation metrics, we followed the common practice to quantitatively evaluate the segmentation performance for automatic methods [Dou *et al.*, 2017]. 对于评估指标，我们遵循通常的做法，对自动方法的分割性能进行了定量评估[Dou等人，2017年]。The DICE coefficient ([%])was employed to assess the agreement between the predicted segmentation and ground truth for cardiac structures. DICE系数([%])被用来评估心脏结构的预测分割与基本事实之间的一致性。We also calculated the average surface distance (ASD[voxel]) to measure the segmentation performance from the perspective of the boundary. 我们还计算了平均表面距离(ASD[体素])，以从边界的角度衡量分割性能。A higher Dice and lower ASD indicate better segmentation performance. Both metrics are presented in the format of *mean*±*std*, which shows the average performance as well as the cross-subject variations of the results.更高的DICE和更低的ASD表示更好的分割性能。这两个指标都以平均值±标准差的形式表示，它显示了平均性能以及结果的跨主体变化。

## Experimental Settings实验设置

In our experiments, the source domain is the MRI images and the target domain is the CT dataset. We demonstrated the effectiveness of the proposed unsupervised cross-modality domain adaptation method with extensive experiments. 在我们的实验中，源域是MRI图像，目标域是CT数据集。我们通过大量的实验验证了所提出的无监督跨模态领域自适应方法的有效性。We designed several experiment settings:我们设计了几个实验设置： 1) training and testing the ConvNet segmenter on source domain (referred as *Seg-MRI*); 在源域上训练和测试ConvNet分割器(简称Seg-MRI)；2) training the segmenter from scratch on annotated target domain data (referred as *Seg-CT*); 在标记的目标域数据(称为Seg-CT)上从头开始训练分割器；3) fine-tuning the source domain segmenter with annotated target domain data, i.e., the supervised transfer learning (referred as *Seg-CT-STL*); 用带标记的目标域数据，即有监督的转移学习(称为Seg-CT-STL)来微调源域分割器；4) directly testing the source domain segmenter on target domain data (referred as *Seg-CT-noDA*); 直接在目标域数据上测试源域分割器(简称Seg-CT-Noda)；5) our proposed unsupervised domain adaptation method (referred as *Seg-CT-UDA*).提出了一种无监督的域自适应方法(简称Seg-CT-UDA)。 We also compared with a previous state-of-the-art heart segmentation method using ConvNets [Payer *et al.*, 2017]. Last but not least, we conducted ablation studies to observe how the adaptation depth would affect the performance.我们还比较了以前使用ConvNets的最先进的心脏分割方法[Payer等人，2017年]。最后但并非最不重要的是，我们进行了消融研究，以观察适应深度对性能的影响。

## Results of Unsupervised Domain Adaptation无监督领域自适应的结果

The results of different methods are listed in Table 1, which demonstrates that the proposed unsupervised domain adaptation method is effective by mapping the feature space of target CT domain to that of source MRI domain. Qualitative results of the segmentations for CT images are presented in Fig. 3.不同方法的结果如表1所示，通过将目标CT域的特征空间映射到源MRI域的特征空间，证明了本文提出的无监督的域自适应方法是有效的。CT图像分割的定性结果如图3所示。

We first evaluate the performance of the segmenter for *SegMRI*, which is the source domain model and serves as the basis for subsequent domain adaptation procedures. 我们首先评估SegMRI的分割器的性能，它是源域模型，并作为后续域适配过程的基础。Compared with the [Payer *et al.*, 2017], our ConvNet segmenter reached promising performance with exceeding Dice on LV-blood and LV-myo, as well as comparable Dice on AA and LA-blood.与[Payer等人，2017]相比，我们的ConvNet分段器在L V-blood和L V-MYO上达到了令人满意的性能，在AA和LA-blood上也达到了可比的Dice。 With this standard segmenter network architecture, we conducted following experiments to validate the effectiveness of our unsupervised domain adaptation framework.在这个标准的分割式网络架构下，我们进行了以下实验来验证我们的无监督领域适配框架的有效性。

To experimentally explore the potential upper-bounds of the segmentation accuracy of the cardiac structures from CT data, we implemented two different settings, i.e., the *Seg-CT* and *Seg-CT-STL*. 为了从CT数据中实验探索心脏结构分割精度的潜在上限，我们实现了两种不同的设置，即Seg-CT和Seg-CT-STL。Generally, the segmenter fine-tuned from *Seg-MRI* achieved higher Dice and lower ASD than the model trained from scratch, proving the effectiveness of supervised transfer learning for adapting an established network to a related target domain using additional annotations. 一般来说，从Seg-MRI微调的分段器比从头开始训练的模型获得了更高的Dice和更低的ASD，证明了有监督转移学习的有效性，可以使用额外的标记使建立的网络适应相关的目标领域。Meanwhile, these results are comparable to [Payer *et al.*, 2017] on most of the four cardiac structures.与此同时，这些结果在四个心脏结构中的大多数上与[Payer等人，2017年]相当。

As for observing the severe domain shift problem inherent in cross-modality biomedical images, we directly applied the segmenter trained on MRI domain to the CT data without any domain adaptation procedure. 为了观察跨模态生物医学图像固有的严重的域漂移问题，我们直接将在MRI域上训练的分割器应用于CT数据，而不需要任何域自适应过程。Unsurprisingly, the network of *Seg-MRI* completely failed on CT images, with average Dice of merely 14.3% across the structures.毫不奇怪，CT图像上的Seg-MRI网络完全失败了，整个结构的平均DICE只有14.3%。

As shown in Table 1,

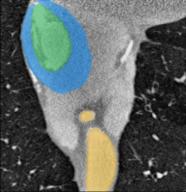
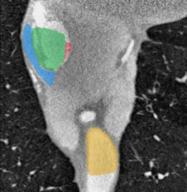
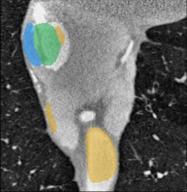
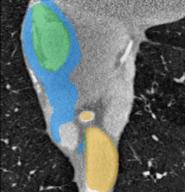
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| |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | | Methods | AA | | LA-blood | | LV-blood | | LV-myo | | | Dice | ASD | Dice | ASD | Dice | ASD | Dice | ASD | | DL-MR [Payer *et al.*, 2017] | 76.6±13.8 | - | 81.1±13.8 | - | 87.7±7.7 | - | 75.2±12.1 | - | | DL-CT [Payer *et al.*, 2017] | 91.1±18.4 | - | 92.4±3.6 | - | 92.4±3.3 | - | 87.2±3.9 | - | | Seg-MRI | 75.9±5.5 | 12.9±8.4 | 78.8±6.8 | 16.0±8.1 | 90.3±1.3 | 2.0±0.2 | 75.5±3.6 | 2.6±1.4 | | Seg-CT | 81.3±24.4 | 2.1±1.1 | 89.1±3.0 | 10.6±6.9 | 88.8±3.7 | 21.3±8.8 | 73.3±5.9 | 42.8±16.4 | | Seg-CT-STL | 78.3±2.8 | 2.9±2.0 | 89.7±3.6 | 7.6±6.7 | 91.6±2.2 | 4.9±3.2 | 85.2±3.3 | 5.9±3.8 | | Seg-CT-noDA | 19.7±2.0 | 31.2±17.5 | 25.7±17.2 | 8.7±3.3 | 0.8±1.3 | N/A | 11.1±14.4 | 31.0±37.6 | | Seg-CT-UDA (*d*=13) | 63.9±15.4 | 13.9±5.6 | 54.7±13.2 | 16.6±6.8 | 35.1±26.1 | 18.4±5.1 | 35.4±18.4 | 14.2±5.3 | | Seg-CT-UDA (*d*=21) | 74.8±6.2 | 27.5±7.6 | 51.1±11.2 | 20.1±4.5 | 57.2±12.4 | 29.5±11.7 | 47.8±5.8 | 31.2±10.1 | | Seg-CT-UDA (*d*=31) | 71.9±0.5 | 25.8±12.5 | 55.2±22.9 | 15.2±8.2 | 39.2±21.8 | 21.2±3.9 | 34.3±19.1 | 24.7±10.5 |   Table 1: Quantitative comparison of segmentation performance on cardiac structures between different methods. (Note: the - means that the results were not reported by that method.)不同方法之间心脏结构分割性能的定量比较。 （注意： - 表示该方法未报告结果。） |

the *Seg-CT-noDA* only got a Dice of 0.8% for the LV-blood. The model did not even output any correct predictions for two of the four testing subjects on the structure of LV-blood (please refer to (e) in Fig. 3). Seg-CT-Noda只有0.8%的LV-blood。该模型甚至没有为四个测试对象中的两个输出任何关于L V-blood结构的正确预测(请参见图3中的(E))。This demonstrates that although the cardiac MRI and CT images share similar high-level representations and identical label space, the significant difference in their low-level characteristics makes it extremely difficult for MRI segmenter to extract effective features for CT.这表明，尽管心脏MRI和CT图像具有相似的高层表示和相同的标签空间，但其低层特征的显著差异使得MRI分割者很难提取出有效的CT特征。

With our unsupervised domain adaptation method, we find a great improvement of the segmentation performance on the target CT data compared with the *Seg-CT-noDA*. 与Seg-CT-Noda算法相比，我们的无监督区域自适应方法在目标CT数据上的分割性能有了很大的提高。More specifically, our *Seg-CT-UDA (d=21)* model has increased the average Dice across four cardiac structures by 43.4%. As presented in Fig. 3, the predicted segmentation masks from *SegCT-UDA* can successfully localize the cardiac structures and further capture their anatomical shapes. 更具体地说，我们的Seg-CT-UDA(d=21)模型使四个心脏结构的平均DICE增加了43.4%。如图3所示，基于SegCT-UDA的预测分割模板可以成功地定位心脏结构，并进一步捕捉其解剖形状。The performance on segmenting AA is even close to that of *Seg-CT-STL*. This reflects that the distinct geometric pattern and the clear boundary of the AA have been successfully captured by the DCM. 对AA的分割性能甚至接近Seg-CT-STL。这反映了清晰的几何图案和清晰的边界已被DCM成功捕捉到。In turn, it supervises the DAM to generate similar activation patterns as the source feature space via adversarial learning. Looking at the other three cardiac structures (i.e., LA-blood, LV-blood and LV-myo), the *Seg-CT-UDA* performances are not as high as that of AA. 反过来，它通过对抗性学习来监督DAM生成与源特征空间相似的激活模式。从其他三种心脏结构(LA-blood、LV-blood和LV-myo)来看，Seg-CT-UDA的性能不如AA。The reason is that these anatomical structures are more challenging, given that they come with either relatively irregular geometrics or limited intensity contrast with surrounding tissues. 原因是这些解剖结构更具挑战性，因为它们要么具有相对不规则的几何形状，要么与周围组织的强度对比有限。The deficiency focused on the unclear boundaries between neighboring structures or noise predictions on relatively homogeneous tissues away from the ROI. 不足之处集中在相邻结构之间的边界不清或远离ROI（感兴趣区域）的相对均匀组织上的噪声预测。This is responsible for the high ASDs of *Seg-CT-UDA*, where boundaries are corrupted by noisy outputs. 这是Seg-CT-UDA的高ASD的原因，其中边界被噪声输出破坏。Nevertheless, by mapping the feature space of target domain to that of the source domain, we obtained greatly improved and promising segmentations against *Seg-CT-noDA* with zero data annotation effort.然而，通过将目标域的特征空间映射到源域的特征空间，我们在不需要进行数据标注的情况下，对Seg-CT-Noda得到了极大的改进和良好的分割效果。

## Ablation Study on Adaptation Depth适应深度的消融研究

The adaptation depth *d* is an important hyper-parameter in our framework, which determines how many layers to be replaced during the plug-and-play domain adaptation procedure.在我们的框架中，适配深度d是一个重要的超参数，它决定了在即插即用域适配过程中需要替换多少层。 Intuitively, a shallower DAM (i.e., smaller *d*) might be less capable of learning effective feature mapping function M across domains than a deeper DAM (i.e., larger *d*). 直观地，较浅的DAM（即，较小的d）比更深的DAM（即，更大的d）可能不太能够学习跨域的有效特征映射函数m。This is due to the insufficient capacity of parameters in shallow DAM, as well



(a) Label (b) d=13 (c) d=21 (d) d=31

Figure 4: Comparison of results using *Seg-CT-UDA* with different adaptation depth (colors are the same with Fig. 3).

as the huge domain shift in feature distributions.这是由于浅DAM中参数的容量不足，以及特征分布中的巨大域移位。 Conversely, with an increase in adaptation depth *d*, DAM becomes more powerful for feature mappings, but training a deeper DAM solely with adversarial gradients would be more challenging. 相反，随着适应深度的增加，对于特征映射，DAM变得更加强大，但仅用对抗梯度训练一个更深的DAM将更具挑战性。Towards this issue, we conducted ablation studies to demonstrate how the performance would be affected by *d*.在这个问题上，我们进行了消融研究，以证明性能如何受到D的影响

To validate above intuitions and search for an optimal *d*, we repeated the experiment with domain adaptation from MRI to CT by varying the *d* = {13*,*21*,*31}, while maintaining all the other settings the same.为了验证上面的直觉并搜索最佳状态，我们通过改变d = {13,21,31}来重复从MRI到CT的域自适应的实验，同时保持所有其他设置相同。 Viewing the examples in Fig. 4, *SegCT-UDA (d=21)* model obtained an approaching ground-truth segmentation mask for ascending aorta. 通过查看图4中的示例，SegCT-UDA(d=21)模型获得了接近真实的升主动脉分割掩模。The other two models also produced inspiring results capturing the geometry and boundary characteristics of *AA*, validating the effectiveness of our unsupervised domain adaptation method. 另外两个模型也得到了令人振奋的结果，捕捉到了AA的几何和边界特征，验证了我们的无监督区域自适应方法的有效性。From the Table 1, we can observe that DAM with a middle-level of adaptation depth (*d=21*) achieved the highest Dice on three of the four cardiac structures, exceeding the other two models by a significant margin. 从表1我们可以观察到，适应深度中等(d=21)的DAM在四个心脏结构中的三个上达到了最高的DICE，显著超过了其他两个模型。For the LA-blood, the three adaptation depths reached comparable segmentation Dice and ASD, and the *d=31* model was the best. 对于LA-blood，三种适应深度都达到了相当的程度分割Dice和ASD，其中d=31模型最好。Notably, the model of *Seg-CTUDA (d=31)* overall demonstrated superiority over the model with adaptation depth *d=13*. This shows that enabling more layers learnable helps to improve the domain adaptation performance on cross-modality segmentations.值得注意的是，Seg-CTUDA(d=31)模型总体上表现出优于适应深度d=13的模型。这表明允许更多的层可学习有助于提高跨模态分割的领域适应性能。

# Conclusion

This paper pioneers to propose an unsupervised domain adaptation framework for generalizing ConvNets across different modalities of biomedical images. The flexible plug-and-play framework is obtained by optimizing a DAM and DCM via adversarial learning. Extensive experiments with promising results on cardiac segmentations have validated the effectiveness of our approach.本文首次提出了一种无监督的领域自适应框架，用于在不同形式的生物医学图像中推广ConvNet。通过对抗性学习对DAM和DCM进行优化，得到灵活的即插即用框架。在心脏分割上取得了令人振奋的结果的广泛实验已经验证了我们方法的有效性。

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