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CSI fingerprinting with SVM regression to achieve device-free passive localization

Device-free crowd counting with WiFi channel state information and deep neural networks

Device-Free Localization Based on CSI Fingerprints and Deep Neural Networks

Device-Free Presence Detection and Localization With SVM and CSI Fingerprinting

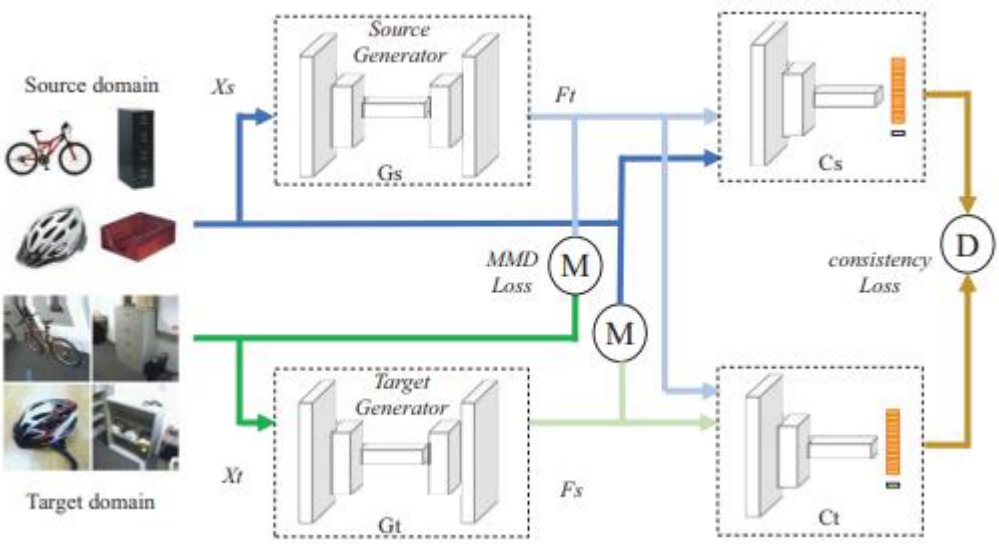
Adaptive Device-free Localization in Dynamic Environments through Adaptive Neural Networks
主要技术： （1）iForest：预处理 （2）多层 CNN 接入 DNN，当作为定位模型，利用来自源域的训练样本，对自适应模型进行训练，当作为域适应模型 （3）Semantic alignment：对相同位置和不同位置的源和目标域 CSI 指纹数据进行对齐。（Euclidean distance 带入训练） 存在问题： 目标域变化与源域差别太小（是否开窗），需要目标域标签 参考： https://en.wikipedia.org/w/index.php?title=Domain_adaptation&action=edit&section=2 https://levelup.gitconnected.com/understanding-domain-adaptation-63b3bb89436f
将源域的 CSI 指纹和目标域中的少量指纹共享到一个共享空间，我们希望从源数据集和目标数据集中提取的特征相似。using the Euclidean distance as the measurement to minimize the distribution mismatch. 用 Domain Adaptation (DA)， Semantic Alignment (SA)技术重新建立新的模型来适应目标域的定位。 AdapLoc consists of a localization model based on onedimensional Convolutional Neural Network (1D-CNN) and a domain adaptation model with Semantic Alignment (SA). AdapLoc adapts the localization model of the source domain using the CSI fingerprints from the source domain and a small number of CSI fingerprints from the target domain, by means of mapping the CSI fingerprints from the source and the target domains into a shared space, with the aim of minimizing the distribution divergence between the two domains. Meanwhile, the source and the target domains are semantically aligned, by minimizing the distance of the mapped fingerprints at the same locations and maximizing the distance of the mapped fingerprints at different locations from the source and the target domains. Its structure is illustrated in Fig. 5. Depending on the input, the adaptive model acts as a localization model or a domain adaptation model. When acting as the localization model, denoted as fR(•), the adaptive model is trained to minimize the localization loss LR in equation (1), using the training samples from the source domain. When acting as the domain adaptation model, denoted as fM(•), the adaptive model without the output layer is trained to minimize the domain loss LD in equation (2), using the training samples from both the source and the target domains （一个模型实现两种函数）

Deep Spatial – Temporal Model Based Cross-Scene Action Recognition Using Commodity WiFi
让志愿者做同样动作十次，每次间隔一段时间，收集 CSI 数据并做预处理，用滑动窗口处理 CSI 数据，将数据带入卷积层和全连接层结合的模型 m1 进行行为识别分类并进行训练(监督学习)，观察结果准确率。取出训练好的 m1 模型中的全连接层作为输入数据带入 Bi-LSTM 模型 m2 进行训练，同样做行为识别分类训练，观察准确率。 微调:(适应新环境) cnn 和 Bi-LSTM 层的参数不做变化，带入新环境的 CSI 数据微调全链接层的参数进行训练 First, in order to capture the spatially local dependencies among CSI channels and adjacent sequences, we divide CSI streams of a sample into multiple segments, from which spatial features are extracted by a CNN model. Then, the original time sequences are converted into CNN feature arrays, each of which denotes spatial features for the corresponding CSI snippet. Furthermore, a Bi-LSTM model which includes The problem can be solved if less new data and computation are required when the scene changes. To address the challenge and improve the robustness to dynamics, we consider a transfer learning algorithm which fine-tunes the new model based on the parameters learned on another similar task instead of training from scratch. In detail, we train our proposed model on the activity recognition task T1 θ (T1) = arg min $\theta \in$Loss(Input(T1), θ) (10) where , Input(T1), and Loss, respectively, denote the parameter domain, input data of T1, and the model loss function. Then, we try to finish another similar task T2 in which the data collection scene and subjects are different from that in T1. In this article, we adopt the transfer learning approach that fine-tunes the parameters θ (T1) trained on T1 for the T2 task θ(T2) = arg min $\theta \in$Loss(Input(T2), θ(T1) + θ) (11) where Input(T2) is the subset of the data collected in T2. In our approach, the parameters of convolutional layers in CNN and Bi-LSTM layers are fixed with only the fully connected layer parameters fine-tuned by a part of data in T2. Consequently, the data demand and computation consumption can be reduced when the scene is transferred.

Bi-Directional Generation for Unsupervised Domain Adaptation

The traditional methods like cycle loss and identity loss in cycleGAN are too restricted for domain adaption. Meanwhile, the previous process in domain adaption only focuses on the global transform. Although it can reduce the distribution difference as cross domain, it destroys the class semantic feature in each sample. It leads to that the classifier trained in this way cannot get the ideal result in the target domain.

Differently, we propose a dual generative cross-domain generation framework by interpolating two intermediate domains to bridge the domain gap. Our proposed method leverages bi-directional cross-domain generators to make two intermediate domains and use additional target data with pseudo labels for learning two task-specific classifiers. Our work is on the exploitation of building bi-directional generation network with two classifiers, which has not been fully explored in the literature.



页码:P6617.(有计算公式和解析)

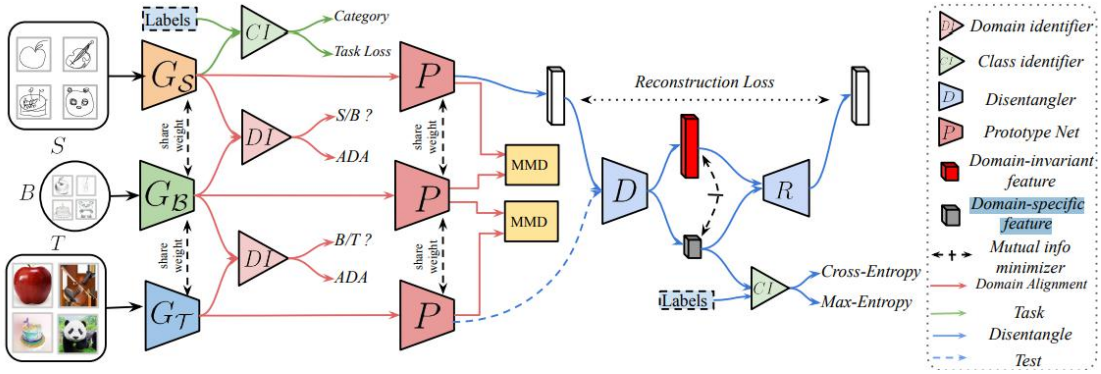
As illustrated in Figure 1, Xs, Xt are source and target samples, respectively. We propose the cross-domain generators Gs, Gt to transfer one domain input to the other domain distribution. Specifically, two generators are defined as Gs : Xs → Xt and Gt : Xt → Xs, respectively. Given the source samples Xs, Gs tries to generate Ft that looks similar to target samples Xt. Similarly, With Xt, Gt aims to generate Fs which looks similar to Xs.

Learning Domain Adaptive Features with Unlabeled Domain Bridges

In this paper, we propose a novel approach to learn domain adaptive features between the largely-gapped source and target domains with unlabeled domain bridges. Firstly, we introduce the framework of Cycle-consistency Flow Generative Adversarial Networks (CFGAN) that utilizes domain bridges to perform image-to-image translation between two distantly distributed domains. Secondly, we propose the Prototypical Adversarial Domain Adaptation (PADA) model which utilizes unlabeled bridge domains to align feature distribution between source and target with a large discrepancy

(1) our approach is devised specifically to tackle the significantly large domain shift, (2) instead of directly synthesizing bridge domains using the source and target domains, we leverage an existing third domain to bridge two distant source and target domains.(是否可以实现跨房间？)

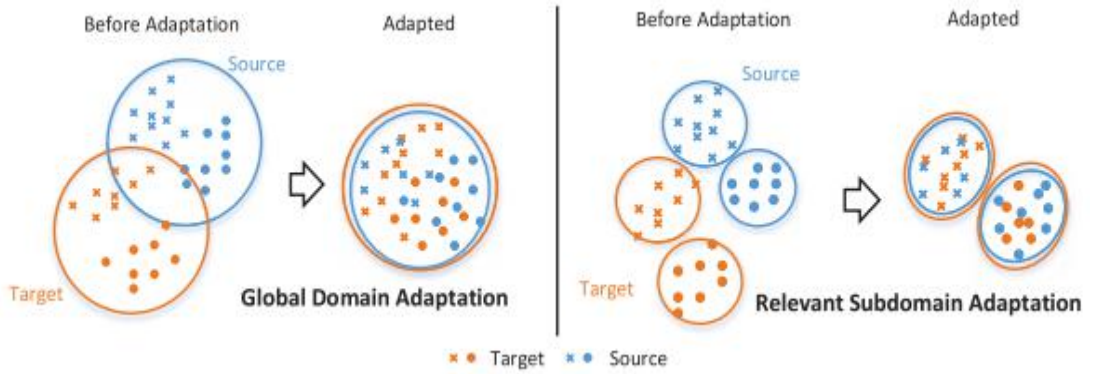
CycleGAN [47] introduces a cycle-consistency loss to recover the original images using a cycle of translation and reverse translation. However, these methods assume that the domain gap between the source and target is relatively small(CycleGAN 用于变化较小的域适应)



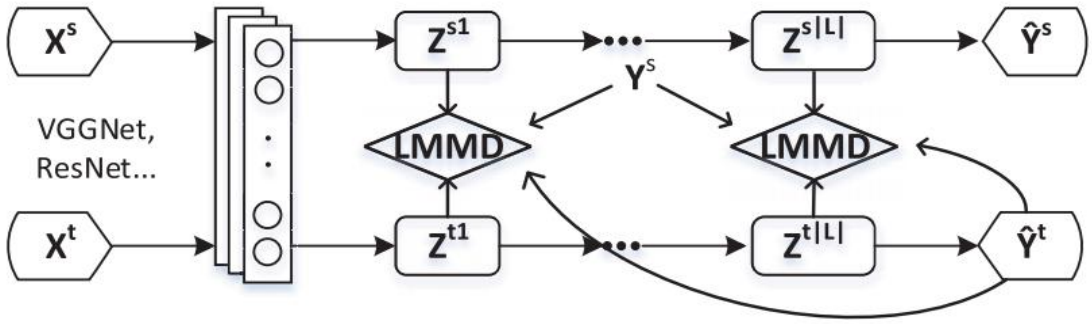
Deep Subdomain Adaptation Network for Image Classification

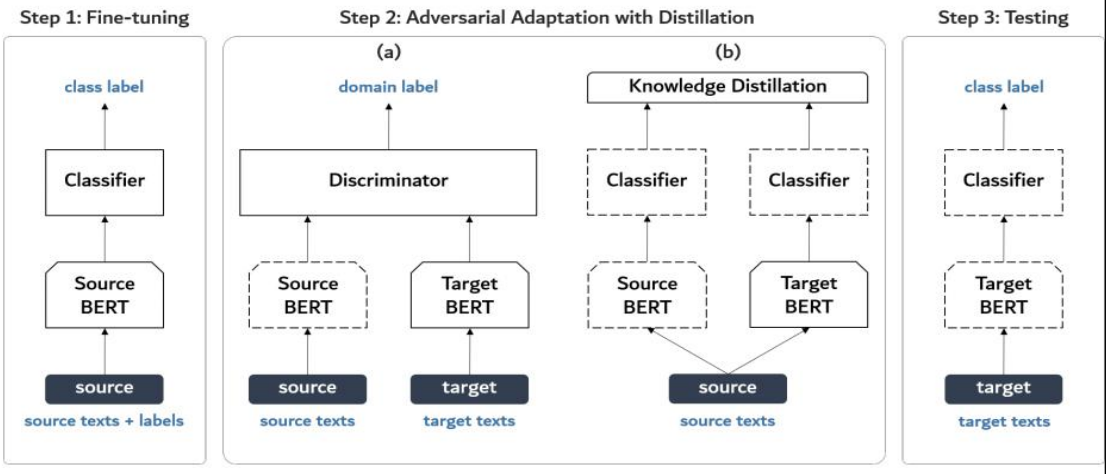
Recently, more and more researchers pay attention to subdomain adaptation that focuses on accurately aligning the distributions of the relevant subdomains. However, most of them are adversarial methods that contain several loss functions and converge slowly. Based on this, we present a deep subdomain adaptation network (DSAN) that learns a transfer network by aligning the relevant subdomain distributions of domain-specific layer activations across different domains based on a local maximum mean discrepancy (LMMD).对抗犹如用一个对抗网络区分两个不同域，从而使两个域分布接近，而 MMD 直接比较生成器生成的域分分布差异来训练。gan 训练完成后，可以通过输入不同的数据生成图片，生成的图片不一定要与区分的图片相同，而是某些特征相同，MMD 则需要对齐两个分布，尤其是 LMMD 分布，对齐两个分布相同标签的域特征

Our code will be available at https://github.com/easezyc/deep-transfer-learning.



Left: global domain adaptation might lose some fine-grained information. Right: relevant subdomain adaptation can exploit the local affinity to capture the fine-grained information for each category.（更加关注子域的对齐，及相同类别和不同类别的域分布，类似于 Adaptive Device-free Localization in Dynamic Environments through Adaptive Neural Networks 中 Semantic Alignment (SA)方法）算法参考论文 p3,p4



Knowledge Distillation for BERT Unsupervised Domain Adaptation
we propose a simple but effective unsupervised domain adaptation method, adversarial adaptation with distillation (AAD), which combines the adversarial discriminative domain adaptation (ADDA) framework with knowledge distillation. We evaluate our approach in the task of cross-domain sentiment classification on 30 domain pairs（情感分类）  $$\mathcal{L}_{KD}(\mathbf{X}_S) = t^2 \times \mathbb{E}_{\boldsymbol{x}_s \sim \mathbb{X}_S} \sum_{k=1}^{K} -\text{softmax}(\boldsymbol{z}_k^S/t) \times \log(\text{softmax}(\boldsymbol{z}_k^T/t))$$ 源码：https://github.com/bzantium/bert-AAD 主要方法：distillation

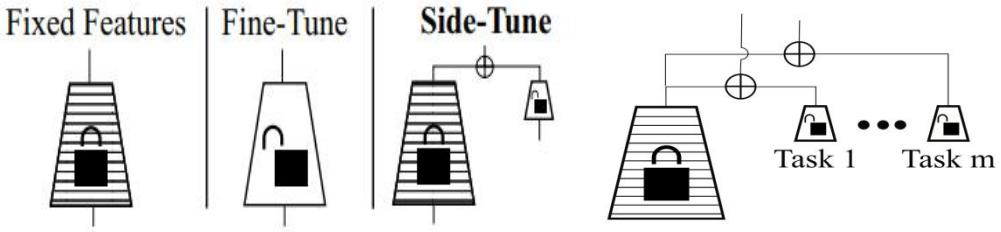
Side-Tuning: A Baseline for Network Adaptation via Additive Side Networks

The goal of side-tuning (and generally network adaptation) is to capitalize on a pretrained model to better learn one or more novel tasks. The side-tuning approach is straightforward: it assumes access to a given (base) model $B : X \rightarrow Y$ that maps the input x onto some representation y. Side-tuning then learns a side model $S : X \rightarrow Y$, so that the curated representations for the target task are

$$R(x) = B(x) \oplus S(x)$$

for some combining operation $\oplus$. For example, choosing $B(x) \oplus S(x) = \alpha B(x) + (1 - \alpha)S(x)$ (commonly called α-blending) reduces the side-tuning approach to: fine-tuning, feature extraction, and stage-wise training, depending on α (Fig. 2, right). Hence those can be viewed as special cases of the side-tuning approach (Figure 1).

Base Model. The base model $B(x)$ provides some core cognition or perception, and we put no restrictions on how $B(x)$ is computed. We never update $B(x)$, and in our approach it has zero learnable parameters.

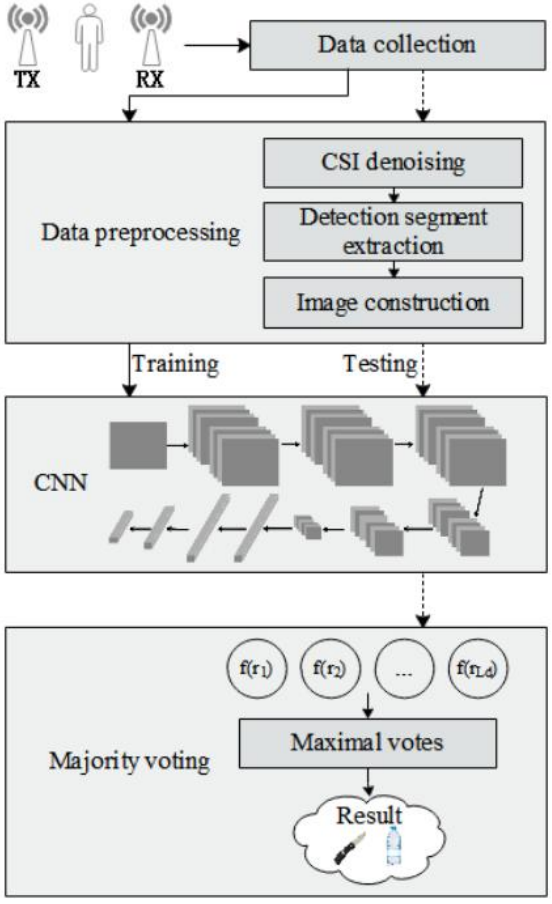


将现有的 fine-tune 机制进行扩展
代码：http://sidetuning.berkeley.edu

$$L(x_t, y_t) = \|D_t(\alpha_t B(x_t) + (1 - \alpha_t)S_t(x_t)) - y_t\|$$

Detection of Suspicious Objects Concealed by Walking Pedestrians Using WiFi

Abstract—Security is of vital importance in public places. Detection of suspicious objects such as metal and liquid often requires dedicated and expensive equipment, preventing its wide deployment. This paper proposes a pervasive device-free method to detect suspicious objects concealed by walking pedestrians using WiFi Channel State Information (CSI). By analyzing the different variations of subcarrier amplitude caused by different materials, the proposed method is able to detect suspicious objects such as metal and liquid concealed by pedestrians, when they walk through the transmission link of the WiFi transmitter and receiver. The proposed method employs Convolutional Neural Network (CNN) to classify suspicious objects, on which majority voting is applied to vote for the final result, in order to improve the detection accuracy for walking pedestrians. Evaluations show that the proposed method with majority voting achieve the detection accuracy of 93.3% for metal and liquid concealed by walking pedestrians, 95.6% for exposed metal and liquid carried by walking pedestrians, and 100% for metal and liquid carried by standing pedestrians.



Wi-Metal: Detecting Metal by Using Wireless Networks 2016 IEEE International Conference on Communications (ICC)

介绍：利用 CSI 数据进行建模实现对不同金属物体的检测，适用于在公共场所的危险物品检测通道。
主要技术：K-Means
Euclidean metric formula (Euclidean distance) as the similarity measure formula and use the sum of squared error formula (SSE) as a measure of clustering quality formula
Euclidean distance:利用欧氏距离公式计算所有数据到聚类中心的距离
SSE:计算的是拟合 数据 和原始数据对应点的误差的平方和

Euclidean distance Formula:

$$L_2[(x_1,...,x_n),(y_1,...,y_n)] = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2}$$

Sum of the Squared Error Formula:

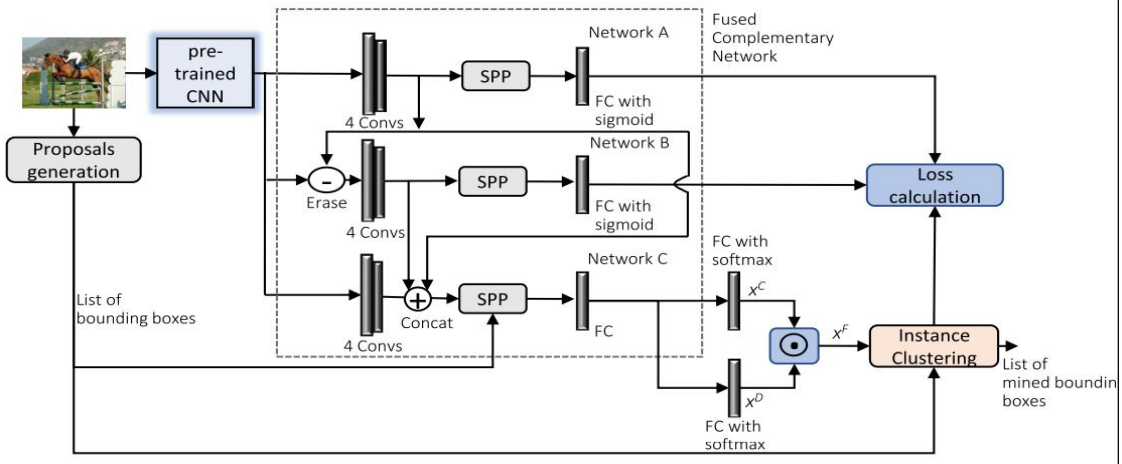
$$SSE = \sum_{i=1}^{k} (x_i - \hat{x}_i)^2$$

Weakly Supervised Object Detection Using Complementary Learning and Instance Clustering

IEEE Access
Year: 2020 | Volume: 8 | Journal Article | Publisher: IEEE

介绍：监督对象检测方案使用完全注释的训练数据，这是相当昂贵的。而弱监督对象检测（WSOD）仅使用图像级别的注释进行训练，这种注释更容易获取。 WSOD是一项具有挑战性的任务，因为它旨在学习使用图像级标签进行对象定位和检测。根据这一主张，在本文中，我们提出了基于判别特征学习的WSOD端到端框架。我们使用客观技术从图像中获取初始建议。然后，并行训练两个互补网络以获得判别式图像特征，这些特征图像将与第三网络的特征在通道上进行级联。我们将此专为区分特征学习而设计的分类网络称为**融合互补网络**。该网络学习通过补充特征将整个对象实例包围起来的建议，这些特征最终将学会预测整个对象比仅包含对象部分的建议具有更高的概率。然后，对区域提议进行分层聚类。我们的聚类方法称为实例聚类，首先执行类间聚类，然后使用“交集-联合”度量执行迭代类内聚类，以获得与每个对象实例相对应的空间相邻聚类成员。在每个类内群集迭代中，将高分建议设置为每个类内群集的质心。在PASCAL VOC2007和PASCAL VOC2012数据集上进行了实验，定性和定量结果均显示在这些基准上WSOD性能得到了改善。

互补学习&实例聚类



spp（金字塔池化）的原理：
spp的做法是使用多个不同大小的sliding window pooling对卷积输出的feature map进行池化，然后将这多个结果进行concat合并得到固定长度的输出。
XC:计算每个区域分类概率
XD:建议待检测区域，利用交叉熵损失
通过分别从分类和检测分支中获取两个得分矩阵xC和xD的Hadamard乘积（元素乘积）来计算最终得分矩阵（xF）
通过以特定于类的方式对区域进行最大池化来从分类分支计算图像级分类分数。然后将聚类应用于提案列表，以获取最终的边界框。

整个网络的损耗函数定义如下：

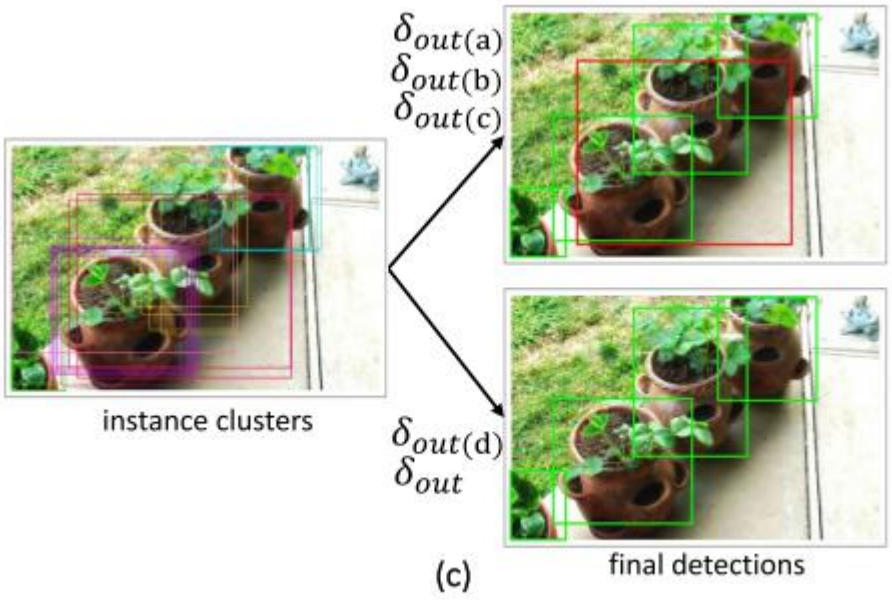
$$L = L_A + L_B + L_C \tag{2}$$

$$L_A = L_B = -\sum_{j=1}^{C} \left(y_{ij}.log\left(p_{ij}\right) + \left(1 - y_{ij}\right).log\left(p_{ij}\right)\right) \tag{3}$$

$$L_C = -\sum_{j=1}^{C} \left(y_{ij}.log\left(p_{ij}\right) + \left(1 - y_{ij}\right).log\left(p_{ij}\right)\right) - \sum_{s=1}^{S} \left(p_s.log\left(p_s\right)\right) \tag{4}$$

其中，L 是所建议的 WSOD 网络的损耗函数，LA，LB 和 LC 分别是网络 A，B 和 C 的损耗函数。 S 是概率分布中离散状态的数量（s 是单个状态）

检测结果：



定性结果（颜色相同的建议表示实例簇）：通过 IC 推断出的中间和最终区域具有不同的异常阈值。 在最终检测中，绿色边界框表示真实检测，红色边界框表示错误检测。 这些检测结果针对单个对象类别进行了演示。

Detecting Suspicious Objects With a Humanoid Robot Having a Metal Detector

介绍：保安机器人需要在机场，仓库，购物中心等场所巡逻，并找到并应对可疑人员。在这项研究中，我们旨在通过类人机器人实现巡逻任务。操作员使用具有金属探测器的人形机器人进行遥控操作，并将探测器摆动到与犯罪嫌疑人衣服表面短距离的位置，并检查衣服下面是否有隐藏的金属物体。为了开发该人体扫描系统，实验确定了取决于摆动速度的金属探测器的测量范围。基于此知识，在 3 种条件下进行了金属物体检测实验：人类，带有/不带有平衡控制的遥控人形机器人。结果表明，仅通过简单的右手的远程控制就不能充分地执行使用金属检测器的类人机器人代替身体搜索工作。因此，有必要集成视觉系统以掌握工作中机器人手的状况以及扩大工作范围的全身配合动作和脚步动作。

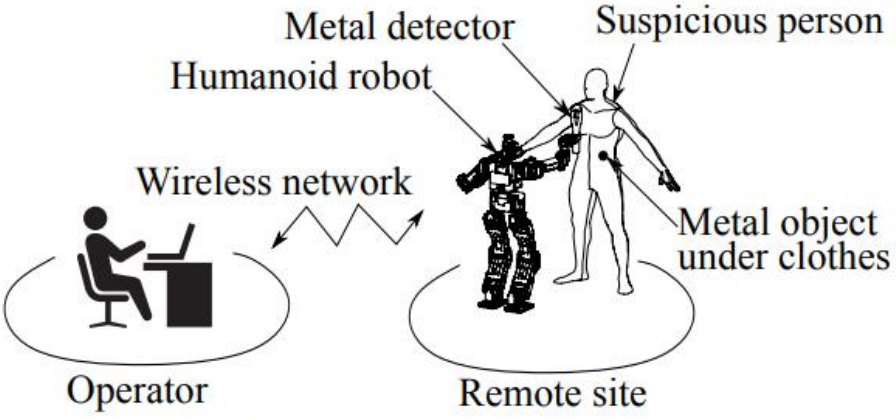


Fig. 1: An overview of body search with a teleoperated humanoid robot.

金属探测器 GC-101H(Doradus Corp.) is used to detect suspicious objects（电流电阻）（动量，角度）

Image-to-Image Translation with Conditional Adversarial Networks

介绍：图像处理、图形学和视觉中的许多问题都涉及到将输入图像转换为相应的输出图像。这些问题通常使用特定于应用程序的算法来处理，尽管设置总是相同的:将像素映射到像素。条件对抗性网(cGAN)是一种通用的解决方案，它似乎能很好地解决各种各样的此类问题。本文介绍基于 cGAN 的 pix2pix 模型，针对不同的图片生成任务进行测试。同时介绍 cycleGAN 技术实现无标签的图片生成任务。

条件 GAN 的目标函数,一般的 cGAN 的目标函数如下，生成器 G 不断的尝试 minimize 下面的目标函数，而 D 则通过不断的迭代去 maximize 这个目标函数，即 G* = arg minG maxD LcGAN (G, D)：

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[\log D(x,y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x,z))],$$

同时也比较一个无条件变量，其中判别器不观察 x:

$$\mathcal{L}_{GAN}(G,D) = \mathbb{E}_{y}[\log D(y)] + \mathbb{E}_{x,z}[\log(1 - D(G(x,z))].$$

将 GAN 目标与更传统的损失混合是有益的。鉴别器的工作保持不变，但生成器的任务不仅欺骗鉴别器，而且在 L2 意义上接近地面真值输出。我在本测试实验中选择使用 L1 距离而不是 L2，因为 L1 可以减少模糊:

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|_1].$$

最终目标函数为:

$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G,D) + \lambda \mathcal{L}_{L1}(G).$$

A Survey of Clustering With Deep Learning: From the Perspective of Network Architecture

介绍：集群是许多数据驱动应用程序领域中的一个基本问题，集群的性能在很大程度上取决于数据表示的质量。因此，线性或非线性特征变换被广泛用于学习更好的聚类数据表示。近年来，大量的研究都集中在利用深度神经网络学习一种对聚类友好的表示，聚类性能得到了显著的提高。在本文中，我们从建筑学的角度对深度学习聚类进行了系统的研究。具体来说，为了更好的理解这一领域，我们首先介绍了初步的知识。在此基础上，提出了一种基于深度学习的聚类方法，并介绍了几种具有代表性的聚类方法。最后，我们提出了一些有趣的机会聚类与深度学习，并给出了一些结论。

Comparison of algorithms based on network architecture and loss function.

Categories	Algorithms	Network Architecture	Network loss	Clustering loss	
				Principal	Auxiliary
AE	DCN	AE	reconstruction loss	k-means loss	N
	DEN	AE	reconstruction loss	N	1) locality-preserving constraint 2) group sparsity constraint
	DSC-Nets	CAE	reconstruction loss	N	self-expressiveness term
	DMC	AE	reconstruction loss	proximity penalty term	locality-preserving loss
	DEPICT	CAE (Denoising)	reconstruction loss	unsupervised cross entropy loss	N
	DCC	AE/CAE	reconstruction loss	robust continuous clustering loss	N
CDNN	DNC	RBM	N	nonparametric maximum margin clustering loss	N
	DEC	FCN	N	cluster assignment hardening loss	N
	DBC	CNN	N	cluster assignment hardening loss	N
	CCNN	CNN	N	k-means	N
	IMSAT	FCN	N	1) regularized information maximization, 2) self-augmented training loss	N
	JULE	CNN	N	agglomerative clustering	N
	DAC[1]	CNN	N	pairwise-classification loss	N
VAE	VaDE	VAE	variational lower bound on the marginal likelihood, with a GMM priori		
	GMVAE	VAE	variational lower bound on the marginal likelihood, with a GMM priori		
GAN	DAC[2]	Adversarial autoencoder	reconstruction loss	1) GMM likelihood, 2) adversarial objective	N
	CatGAN	GAN	adversarial objective with a multi-classes priori		
	InfoGAN	GAN	adversarial objective with a multi-classes priori		

[1] Deep Adaptive Clustering
[2] Deep Adversarial Clustering

Main contributions of the representative algorithms.

Categories	Algorithms	Main contributions to clustering
AE	DCN	perform k-means clustering and feature learning simultaneously, simple but effective
	DEN	learn a clustering-friendly representation
	DSC-Nets	improve the classical subspace clustering by AE
	DMC	improve the classical multi-manifold clustering by AE
	DEPICT	computational efficient, robust, perform well on image datasets
	DCC	avoid alternative optimization, require no prior knowledge of cluster number
CDNN	DNC	improve the classical NMMC clustering by DBN
	DEC	the first well-known deep clustering method, making this field popular
	DBC	improve DEC using CNN
	CCNN	computational efficient, deal with large-scale image datasets
	IMSAT	introduce self-augment training to deep clustering
	JULE	perform well on image datasets, but have high computational and memory cost
	DAC	well-designed clustering loss, achieve the-state-of-art performance on several datasets
VAE	VaDE	combine VAE with clustering
	GMVAE	combine VAE with clustering
GAN	DAC	combine AAE with clusteirng
	CatGAN	combine GAN with clustering
	InfoGAN	learn disentangled representations

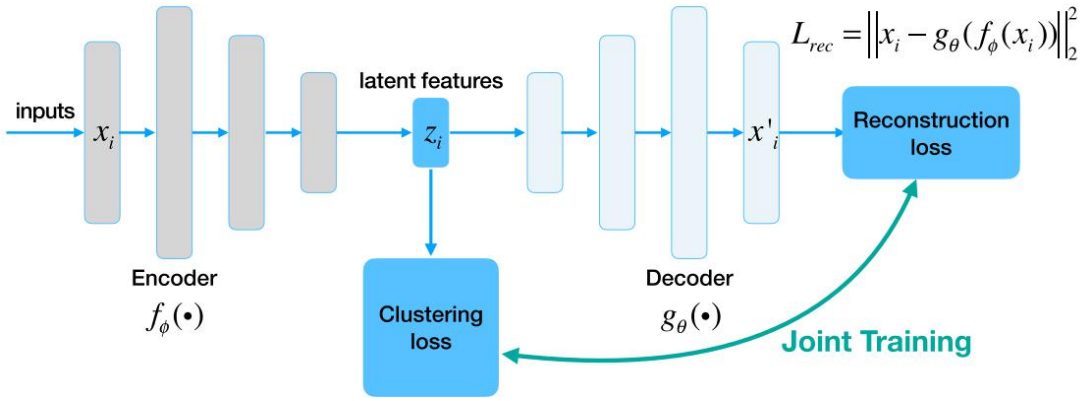


FIGURE 1. Architecture of clustering based on autoencoder. The network is trained by both clustering loss and reconstruction loss.

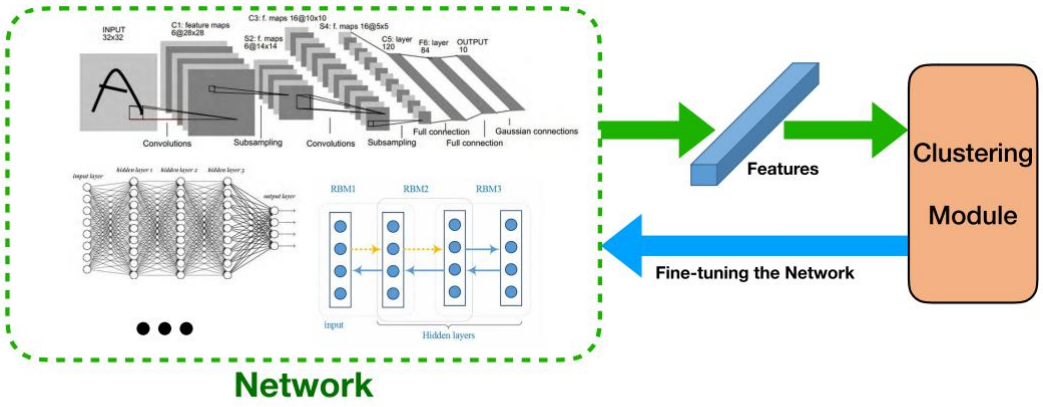


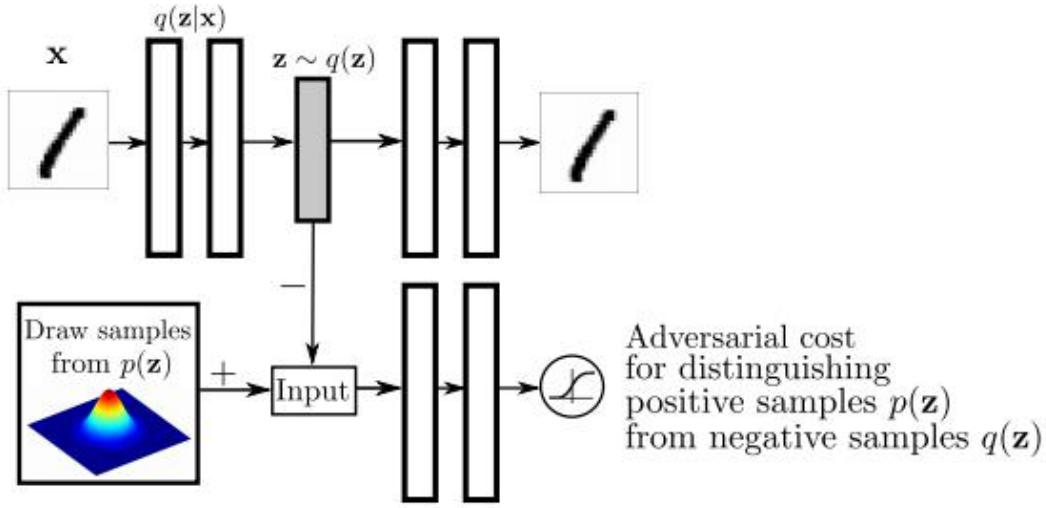
FIGURE 2. Architecture of CDNN-based deep clustering algorithms. The network is only adjusted by the clustering loss. The network architecture can be FCN, CNN, DBN and so on.

Adversarial Autoencoders

A. Makhzani, J. Shlens, N. Jaitly, I. Goodfellow, and B. Frey. (2015). ‘‘Adversarial autoencoders.’’ [Online]

该文提出“对抗式自动编码器”(AAE)，这是一种概率式的自动编码器，它利用新提出的生成式对抗网络(GAN)，以任意先验分布匹配自编码器隐藏码向量的后验集合来进行变分推理。将聚集的后验与先验进行匹配，可确保从先验空间的任何部分生成有意义的样本。因此，对抗性自动编码器的解码器学习了一个深度生成模型，该模型在数据分布之前映射施加的数据。我们展示了对抗式自动编码器如何在半监督分类、图像解缠风格和内容、无监督聚类、降维和数据可视化等应用中使用。我们在 MNIST、街景房屋号码和多伦多人脸数据集上进行了实验，结果表明对抗自动编码器在生成建模和半监督分类任务中取得了具有竞争力的结果。

目的：1 使隐藏向量更具有区分性.2 使隐藏向量能生成更加完整分布



$$\min_G \max_D \mathrm{E}_{\mathbf{x}\sim p_{\text{data}}}[\log D(\mathbf{x})] + \mathrm{E}_{\mathbf{z}\sim p(\mathbf{z})}[\log(1 - D(G(\mathbf{z}))]$$

生成器 G 的编码器和下方判别器 D 组成的对抗网络，此处 G 和 D 联系起来的不再是图片数据，而是一个一维向量 z，判别器 D 通过不断学习，预测输入的 z 来自于 real data（服从 q(z)概率分布）还是 fake data（服从预定义的 p(z)概率分布）。由于这里的 p(z)可以是任何我们可以生成的一个概率分布，因此整个对抗学习过程实际上可以认为是通过调整 encoder 不断让其产生数据的概率分布 q(z)接近我们预定义的 p(z)，当模型训练完成后，由于 p(z)与 q(z)十分相近，因此可以直接通过 p(z)产生我们需要的随机 latent variable，然后借助于解码器产生一个新的图像数据。Adversarial Latent Autoencoders

Adversarial Latent Autoencoders CVPR 2020

我们设计了两个自动编码器:一个基于MLP编码器,另一个基于StyleGAN生成器,我们称之为StyleALAE。我们验证了这两个架构的解纠缠特性。结果表明,StyleALAE不仅可以生成与StyleGAN相当质量的1024×1024人脸图像,而且在相同分辨率下,还可以生成基于真实图像的人脸重建和处理。这使得ALAE成为第一个能够与之相比的自动编码器,并且超越了仅产生器类型的架构的能力。

生成图片能力与StyleGAN相当

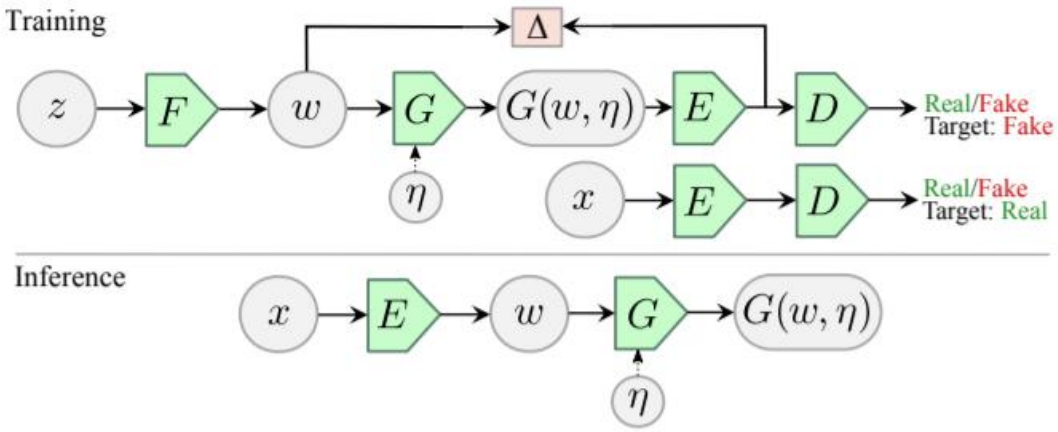


Figure 1: **ALAE Architecture.** Architecture of an Adversarial Latent Autoencoder.

把原生GAN中的G分解为F与G的映射,D分解为E与D的映射:

$$\mathtt{G} = G \circ F\,, \quad \text{and} \quad \mathtt{D} = D \circ E$$

F是一个确定性的映射,将噪声z编码成隐变量w。E和G是随机的,G同时取决于隐变量w和噪声的输入。E将生成的图像进行编码,然后约束由F生成的分布与由E生成的分布尽可能详尽。这样给定w就可以生成图像,给定图像就可以编码w。在推理时就可以实现重构。可以看到公式7约束的就是隐变量空间w的相似度,而非约束原生AE中的图像(数据空间)相似度。

$$\min_{F,G} \max_{E,D} V(G \circ F, D \circ E) \qquad (6)$$

$$\min_{E,G} \Delta(F \| E \circ G \circ F) \qquad (7)$$

上式即为目标函数。相比BiGAN重构效果不太受到label filp的影响:

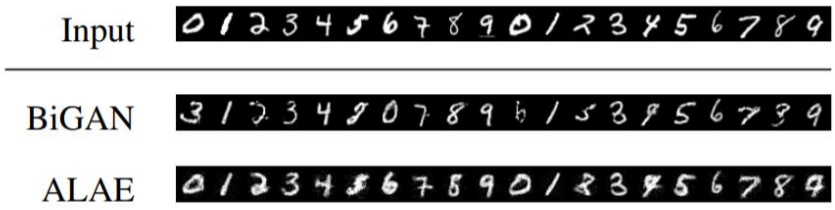


Figure 3: **MNIST reconstruction.** Reconstructions of the permutation-invariant MNIST. Top row: real images. Middle row: BiGAN reconstructions. Bottom row: ALAE reconstructions. The same MLP architecture is used in both methods.

对比在 Z 空间插值和直接在 W 空间插值的结果：后者更平滑，较为分离。

Figure 4: **MNIST traversal.** Reconstructions of the interpolations in the $\mathcal{Z}$ space, and the $\mathcal{W}$ space, between the same digits. The latter transition appears to be smoother.

基于 StyleGan 的结构：

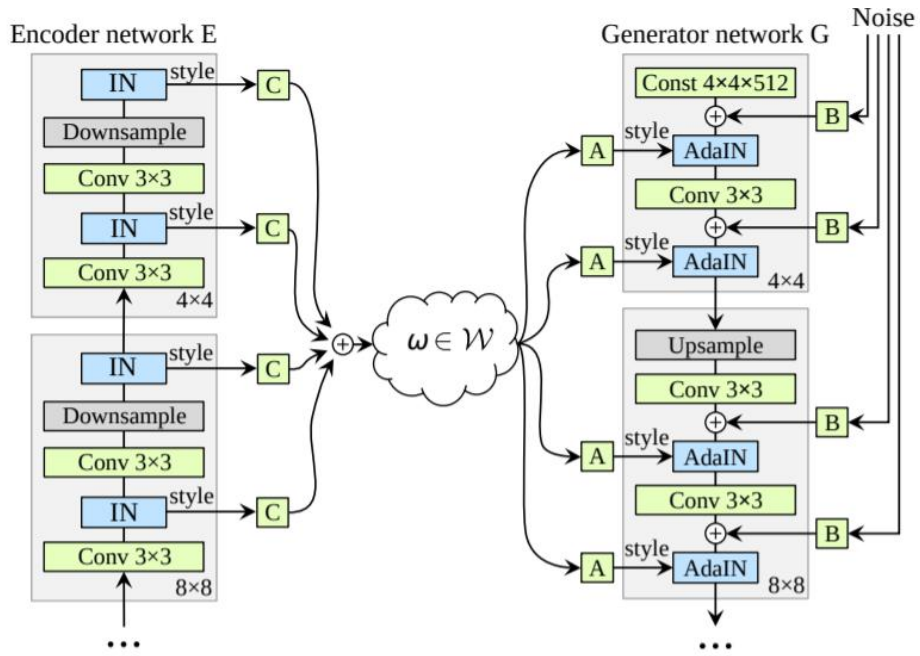


Figure 2: **StyleALAE Architecture.** The StyleALAE encoder has Instance Normalization (IN) layers to extract multiscale style information that is combined into a latent code w via a learnable multilinear map.

各级风格特征（均值方差）经过一个线性层来聚合后放到 GAN 里，此时的 E 就可以编码风格，重建效果：

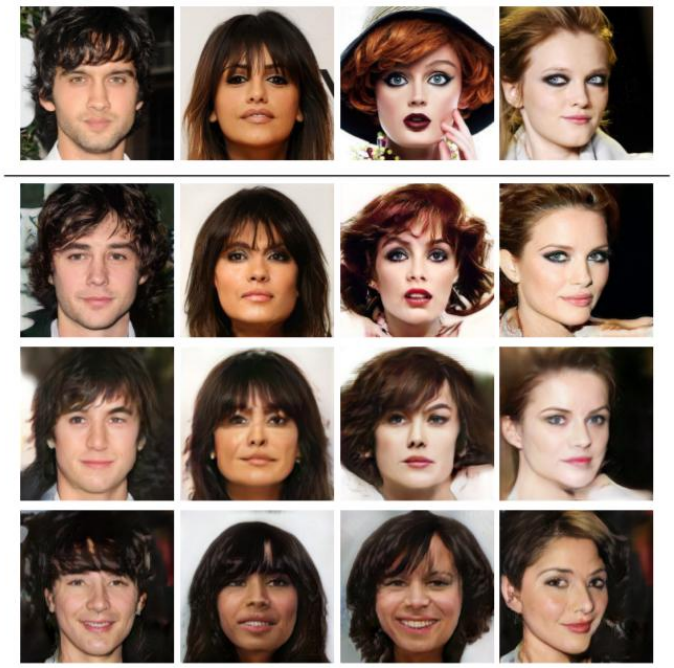


Figure 8: **CelebA-HQ reconstructions.** CelebA-HQ reconstructions of unseen samples at resolution 256×256. Top row: real images. Second row: StyleALAE. Third row: Balanced PIONEER [17]. Last row: PIONEER [16]. StyleALAE reconstructions look sharper and less distorted.