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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

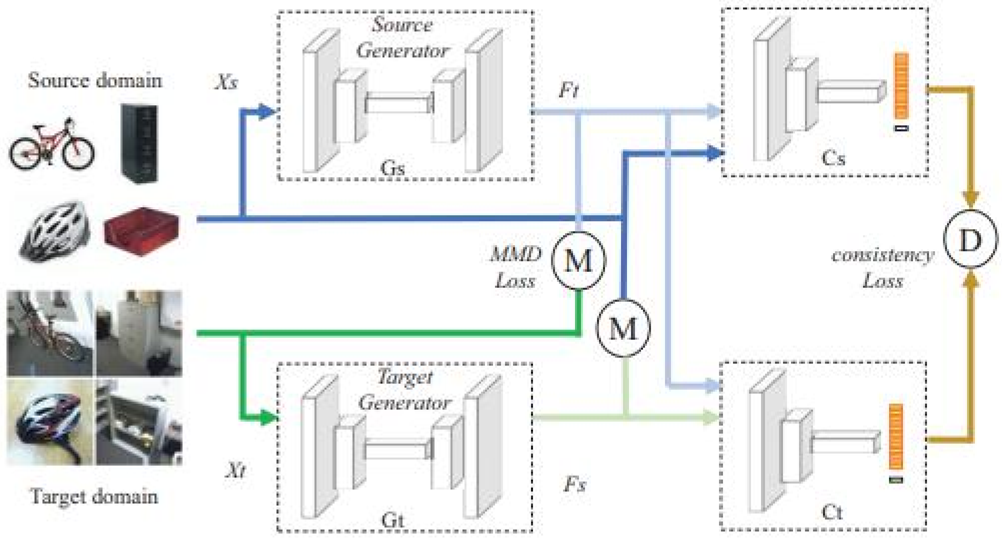
Adaptive Device-free Localization in Dynamic Environments through Adaptive Neural Networks
主要技术： （1）iForest：预处理 （2）多层 CNN 接入 DNN，当作为定位模型，利用来自源域的训练样本，对自适应模型进行训练，当作为域适应模型 （3）Semantic alignment：对相同位置和不同位置的源和目标域 CSI 指纹数据进行对齐。（Euclidean distance 带入训练） 存在问题： 目标域变化与源域差别太小（是否开窗），需要目标域标签 参考： https://en.wikipedia.org/w/index.php?title=Domain_adaptation&action=edit&section=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 θ ∈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 θ ∈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)

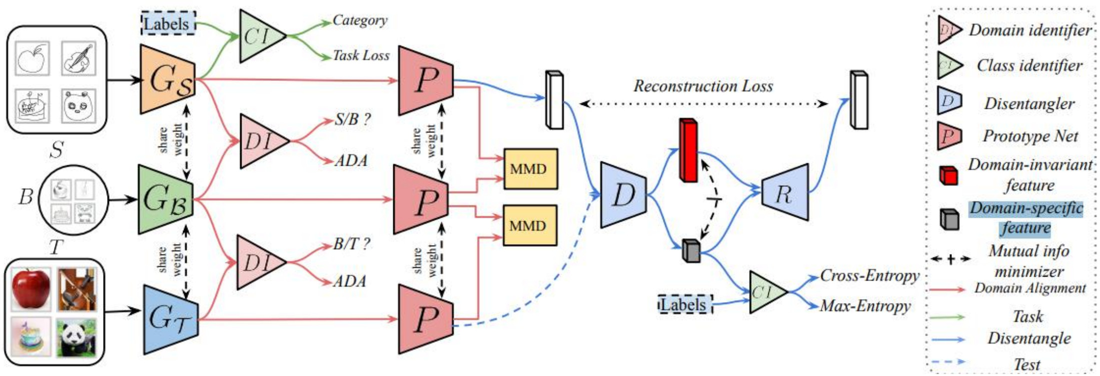
As illustrated in Figure 1, Xs, Xt are source and target samples, respectively. We propose the cross-domain generators Gs, Gt to transfer one domain input to the other domain distribution. Specifically, two generators are defined as Gs : Xs → Xt and Gt : Xt → Xs, respectively. Given the source samples 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？)

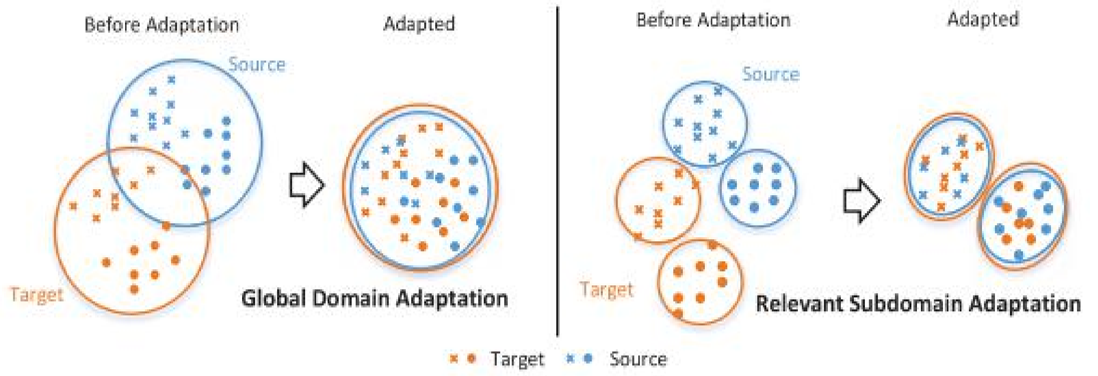
CycleGAN [47] introduces a cycle-consistency loss to recover the original images using a cycle of translation and reverse translation. However, these methods assume that the domain gap between the source and target is relatively small(CycleGAN 用于变化较小的域适应)



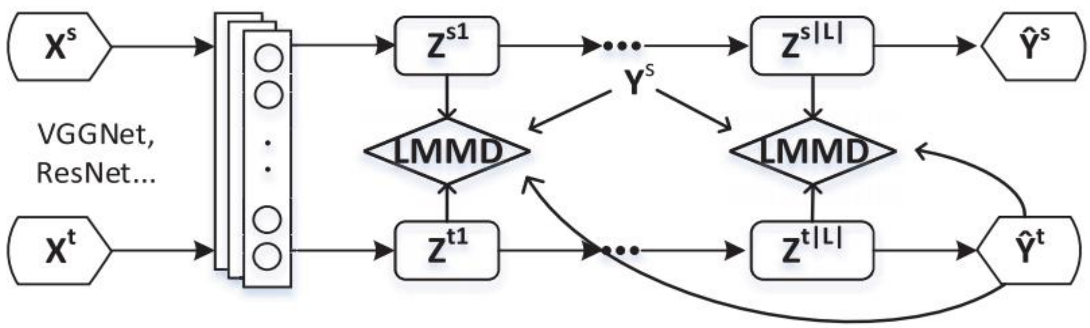
Deep Subdomain Adaptation Network for Image Classification

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.

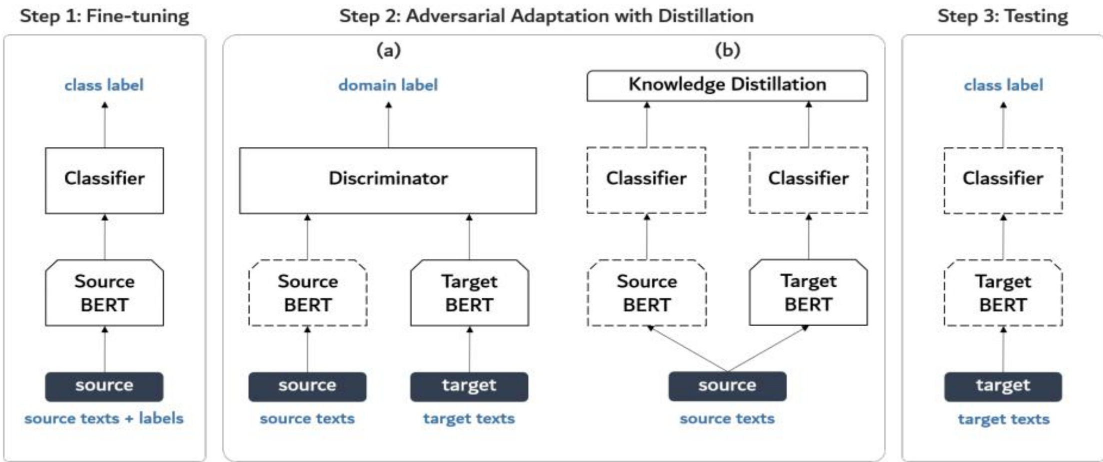


Left: global domain adaptation might lose some fine-grained information. Right: relevant subdomain adaptation can exploit the local affinity to capture the fine-grained information for each category.（更加关注子域的对齐，及相同类别和不同类别的域分布，类似于 Adaptive Device-free Localization in Dynamic Environments through Adaptive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



$$\mathcal{L}_{KD}(\mathbf{X}_S) = t^2 \times \mathbb{E}_{\boldsymbol{x}_s \sim \mathbf{X}_S} \sum_{k=1}^{K} -\text{softmax}(z_k^S/t) \times \log(\text{softmax}(z_k^T/t))$$

源码：https://github.com/bzantium/bert-AAD

主要方法：distillation

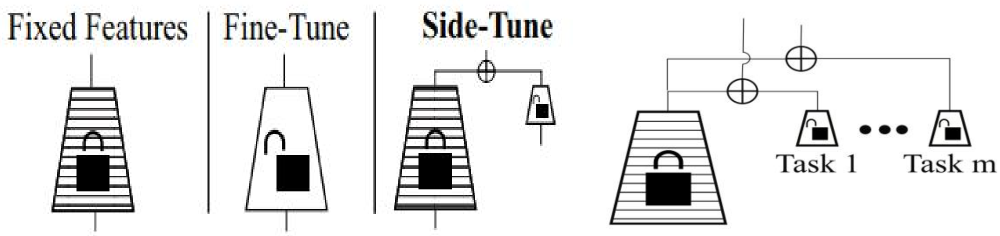
Side-Tuning: A Baseline for Network Adaptation via Additive Side Networks

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 → Y that maps the input x onto some representation y . Side-tuning then learns a side model S : X → Y, so that the curated representations for the target task are

R(x) =B(x) ⊕ S(x)

for some combining operation ⊕. For example, choosing B(x) ⊕S(x) = α B(x) + (1 − α)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.