Unsupervised Domain Adaptation for Remote Sensing Images Using Metric Learning and Correlation Alignment

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Overview

- Domain Adaptation is a problem in Remote Sensing image analysis.
- Models proposed till now consider only one of :
  - the discriminativeness of the embedding space
  - usefulness of a manifold distance is pulling the domains closer

  not both together.

Goal: To learn a latent space that aligns of similar classes across different domains with high precision.

Problem Statement

- **Given:**
  - source domain items with class labels.
  - target domain items without class labels.
- **Task:** Predict class labels for items in target domain (ground truth not available)

Motivation

- Clustering improves classification.
- The feature space should be discriminative.
  - Less intraclass more interclass distance

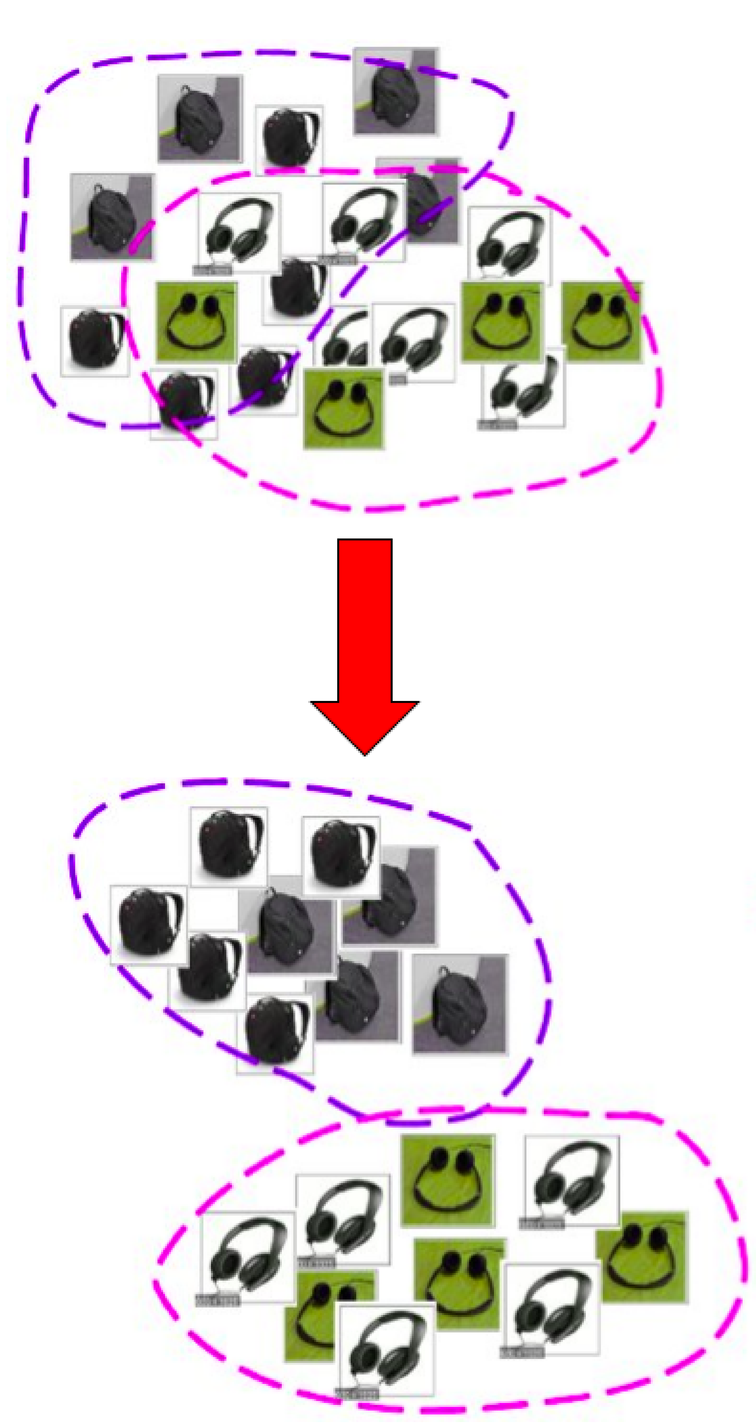

Figure 1:Motivation behind our approach with example of bags and headphones

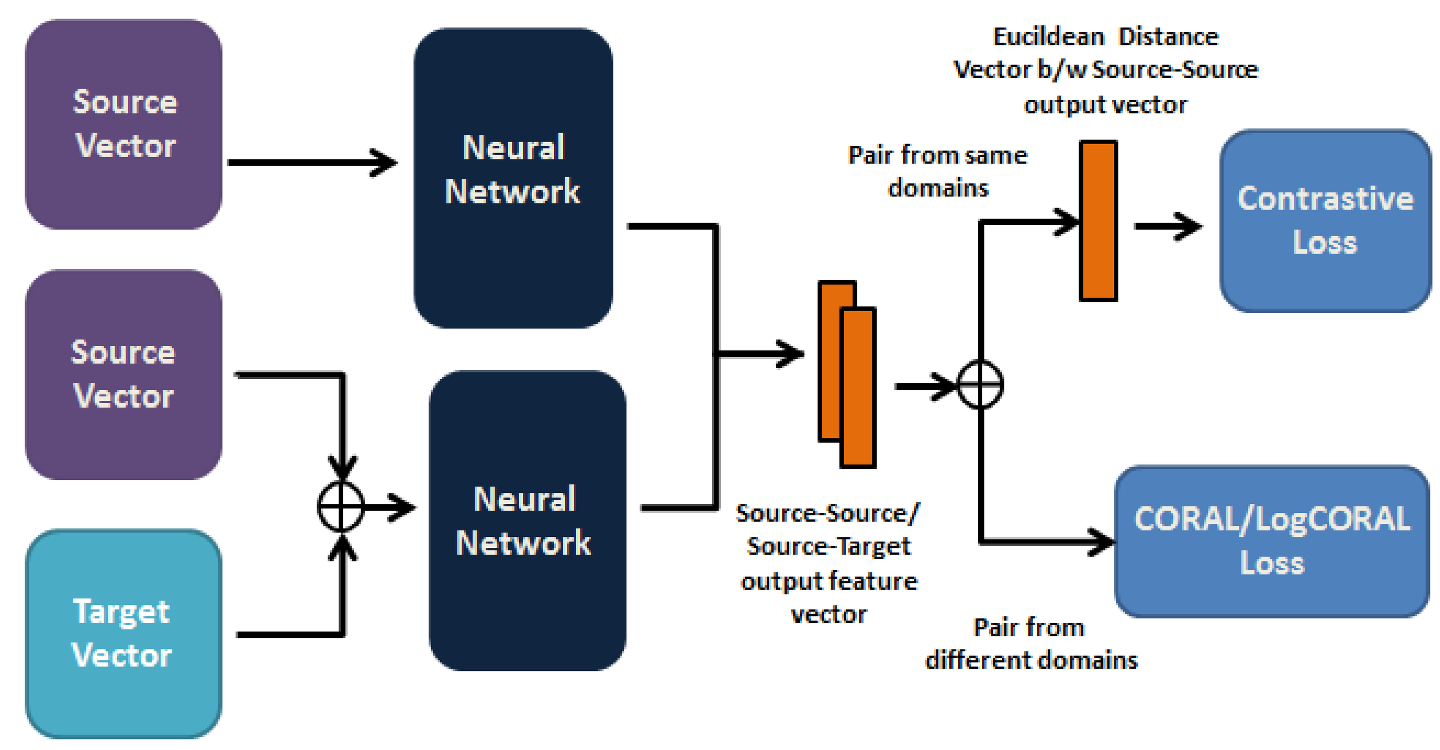

Figure 2:Overview of our model

Metric Learning

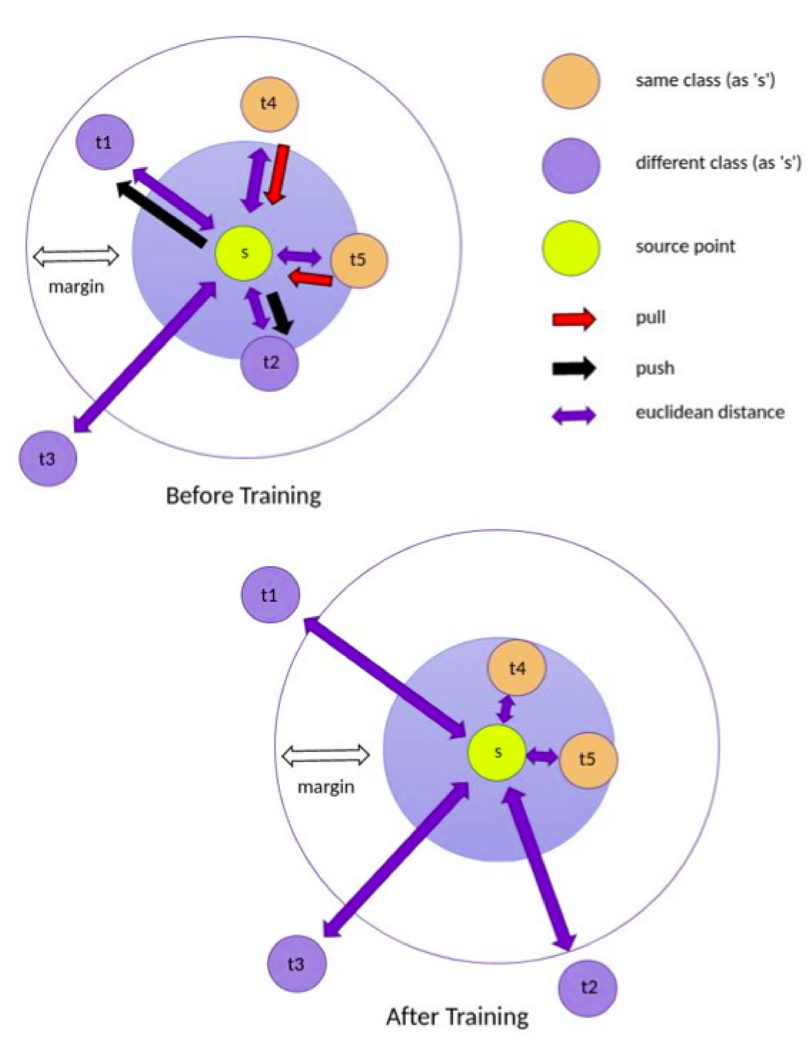

Figure 3:Process of clustering

- Class labels of source data items is the basis of creation of clusters.
- Contrastive loss used for minimising the distance between similar class objects and increase the distance between dissimilar class objects in euclidean manifold.

Datasets

Dataset	Domain	Train	Test
2*Botswana	Domain1	1242	1252
	Domain2	2621	627
2*Pavia	Pavia Centre	50000	22933
	Pavia University	20000	19332

Table 1:Table mentioning features of 2 datasets used for evaluation of our algorithm

- The number of spectral bands in both the datasets are :
  1. Botswana (Domain 1) : 10
  2. Botswana (Domain 2) : 10
  3. Pavia Centre : 102
  4. Pavia University : 103

Correlation Alignment

- To align source and target domain, we reduce covariance between them.
- Used 2 types of loss functions :
  1. **CORAL:** minimize distance between covariance matrices of source and target domain in Euclidean space.
  $$L_{CORAL} = \frac{1}{4d^2}||\mathbf{C_S} - \mathbf{C_T}||^2 \quad (1)$$
  2. **logCORAL:** minimize distance between covarinace matrices of source and target domain in Riemannian manifold.
  $$L_{logCORAL} = \frac{1}{4d^2}||log(\mathbf{C_S}) - log(\mathbf{C_T})||^2 \quad (2)$$
- Where $\mathbf{C_S}$ is the covariance matrix of source domain and $\mathbf{C_T}$ is the covariance matrix of the target domain

Method

- Minimizing the Clustering loss itself is going to over-fit for the source domain and give poor clustering for the target domain.
- reducing the Covariance loss would lead to degenerate features as the network will project all the source and target data to a single point leading to zero Covariance.
- We jointly train the network on Covariance loss with Clustering loss to learn the desirable domain invariant mapping.
- The two losses play counterparts and reach an equilibrium at the end of the training, where the final features are expected to work well on the target domain.

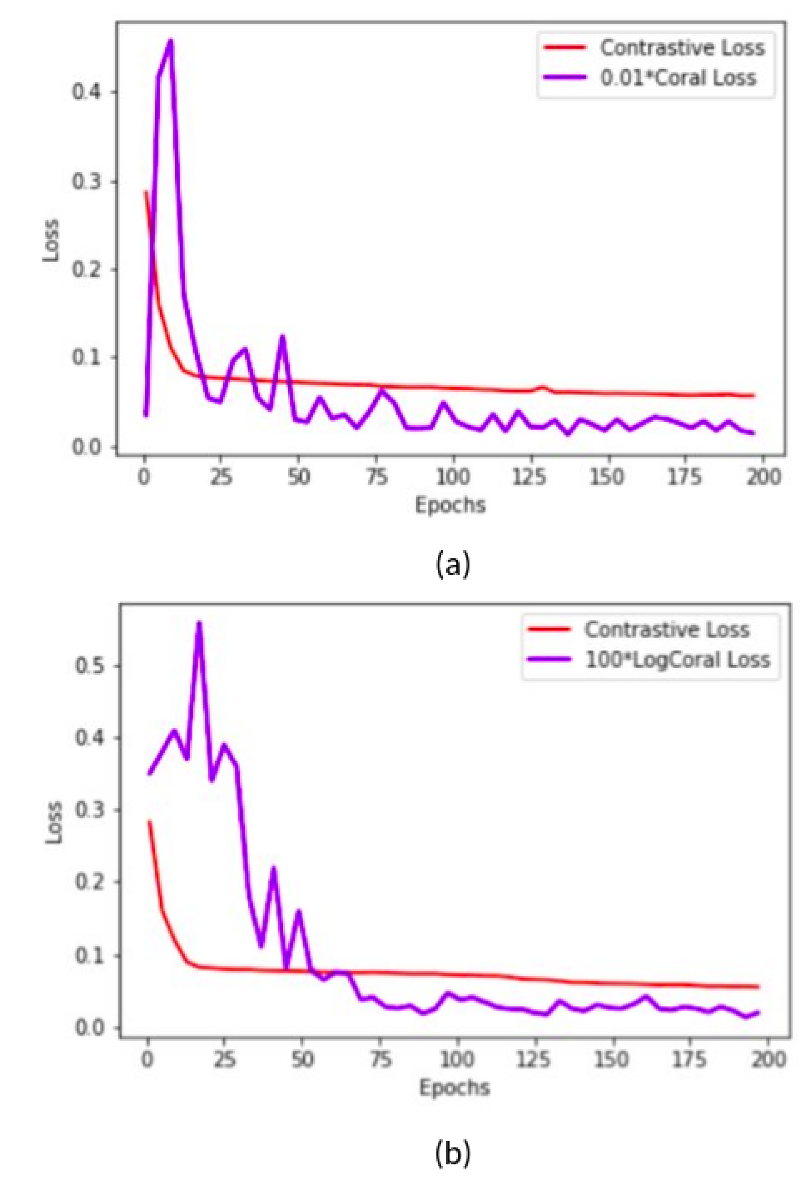

Figure 4:Loss curves of (a) Contrastive loss with CORAL loss and (b) Contrastive loss logCORAL loss

Quantative Results

Model	TR1→TS2	TR2→TS1
TCA	69.88	61.00
GFK	72.89	65.50
CORAL	54.54	47.36
SA	72.88	68.52
STK	75.28	70.20
BDA	62.52	50.72
Auto-Encoder	67.46	62.69
Deep-LogCORAL	75.09	68.48
our(CORAL)	76.08	69.73
our(LogCORAL)	**76.24**	**71.09**

Table 2:Performance comparison of our model with baseline models in domain adaptation on Botswana dataset.

Model	PaviaC→PaviaU	PaviaU→PaviaC
Auto-Encoder	46.14	46.64
Deep-LogCORAL	47.57	51.28
our(CORAL)	47.72	45.86
our(LogCORAL)	**47.81**	**56.32**

Table 3:Performance comparison of our model with Auto-Encoder(w/ Auxiliary Loss) on Pavia dataset.

Conclusion & Future Work

- Similarity learning with reduced co-variance better than simple classification or ML based approaches.
- We look forward to applying different approaches like
  1. Similarity learning based on data distribution, not just class labels
  2. Expanding our method to other standard domain adaptation datasets.