

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



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# Problem Statement

- Importance of Remote Sensing Image Analysis :
  - Real-time monitoring of agricultural crops
  - Mapping forest fires
  - Tracking clouds for weather prediction
  - Tracking city growth

# Problem Statement

## 1. Season change

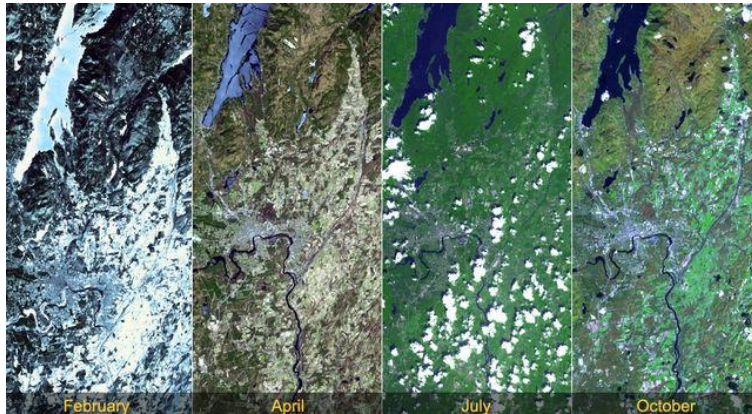


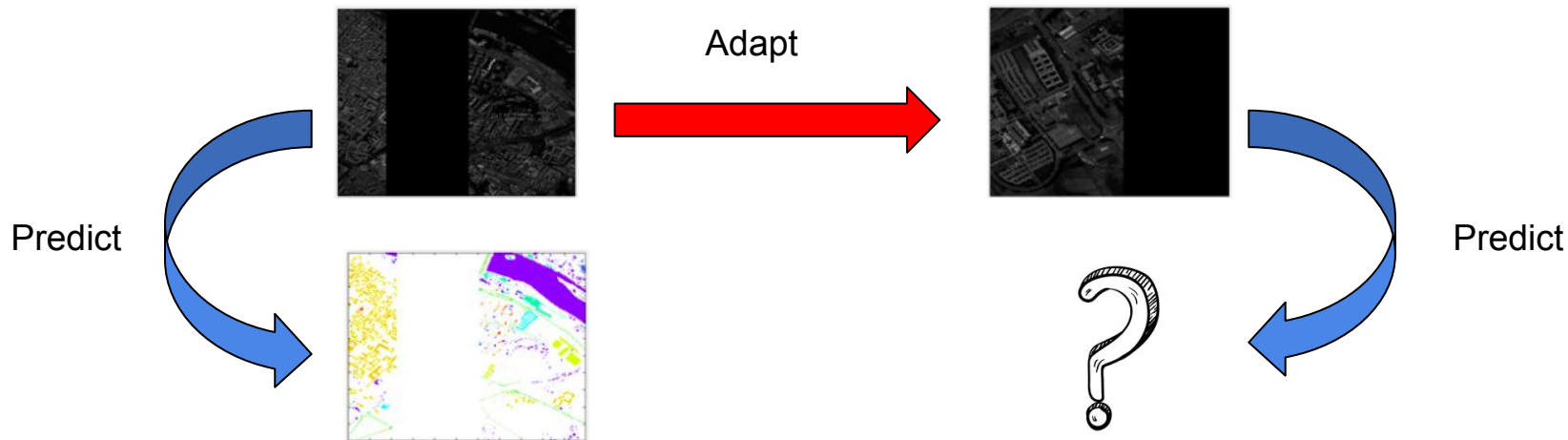
Fig. Seasonal changes over particular land area

## 2. Cloud formation



Fig. Cloud formation over land

# Problem Statement



Source Domain  $\sim P_S(X, Y)$

lots of **labeled** data

$$D_S = \{(\mathbf{x}_i, y_i), \forall i \in \{1, \dots, N\}\}$$

$\neq$

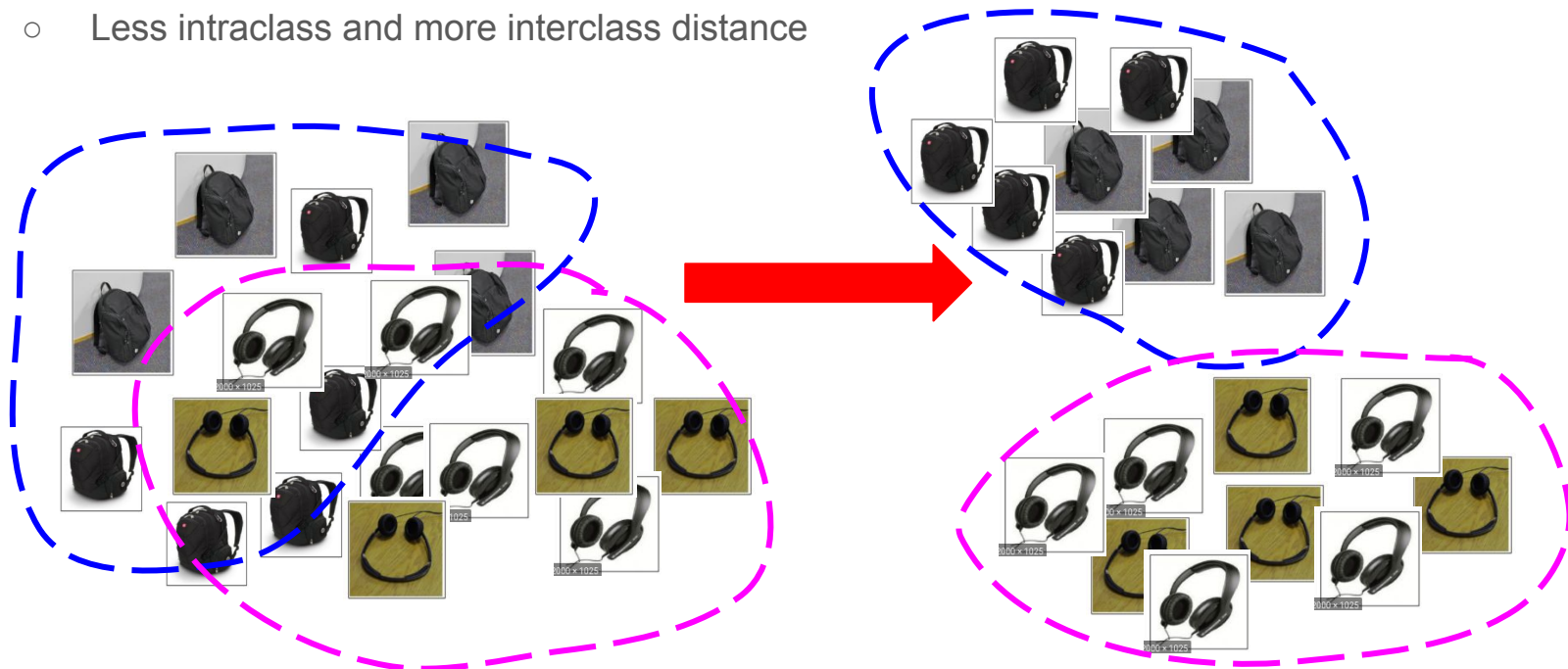
Target Domain  $\sim P_T(Z, H)$

unlabeled or limited labels

$$D_T = \{(\mathbf{z}_j, ?), \forall j \in \{1, \dots, M\}\}$$

# Motivation

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



# Proposed Model for Source Domain

- Source Embedding Network

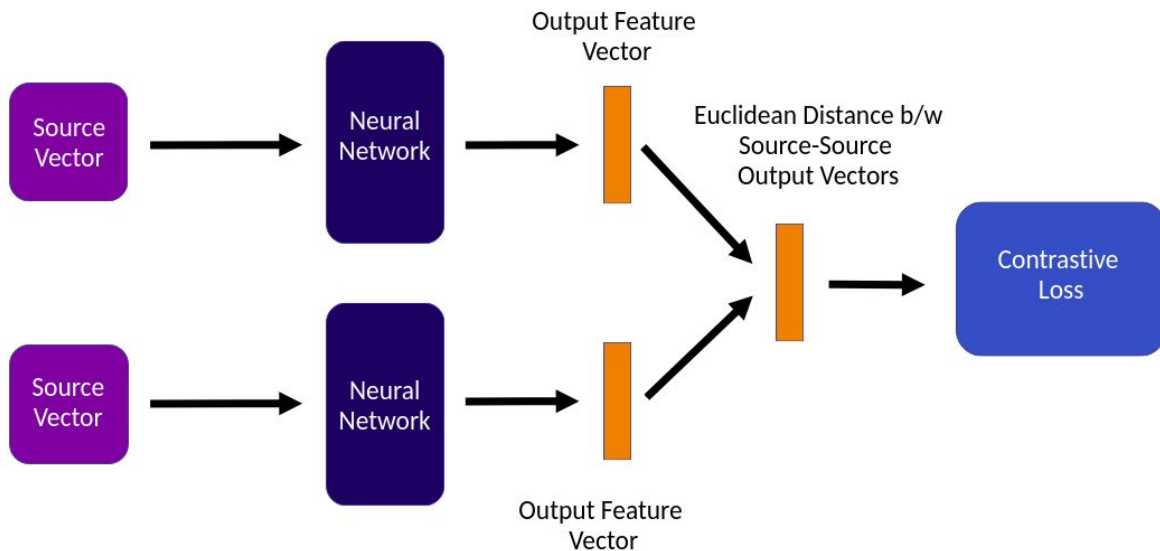
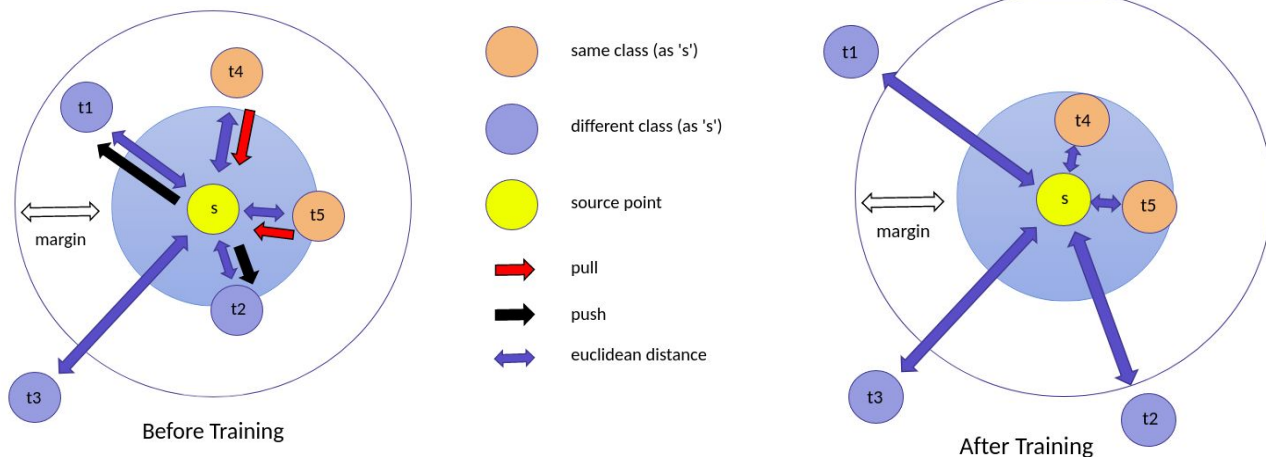


Fig. Network overview for Clustering

# Proposed Model for Source Domain

- Contrastive Loss

$$D_W(\mathbf{X}_1, \mathbf{X}_2) = ||G_W(\mathbf{X}_1) - G_W(\mathbf{X}_2)||$$



$$L(W, (Y, \mathbf{X}_1, \mathbf{X}_2))^i = (1 - Y)L_S(D_W^i) + Y \max(0, m - L_D(D_W^i))$$

$$\kappa(W) = \sum_{i=1} L(W, (Y, \mathbf{X}_1, \mathbf{X}_2))^i$$

# Proposed Model Correlation Alignment

- Cross-Domain Correlation Alignment Network

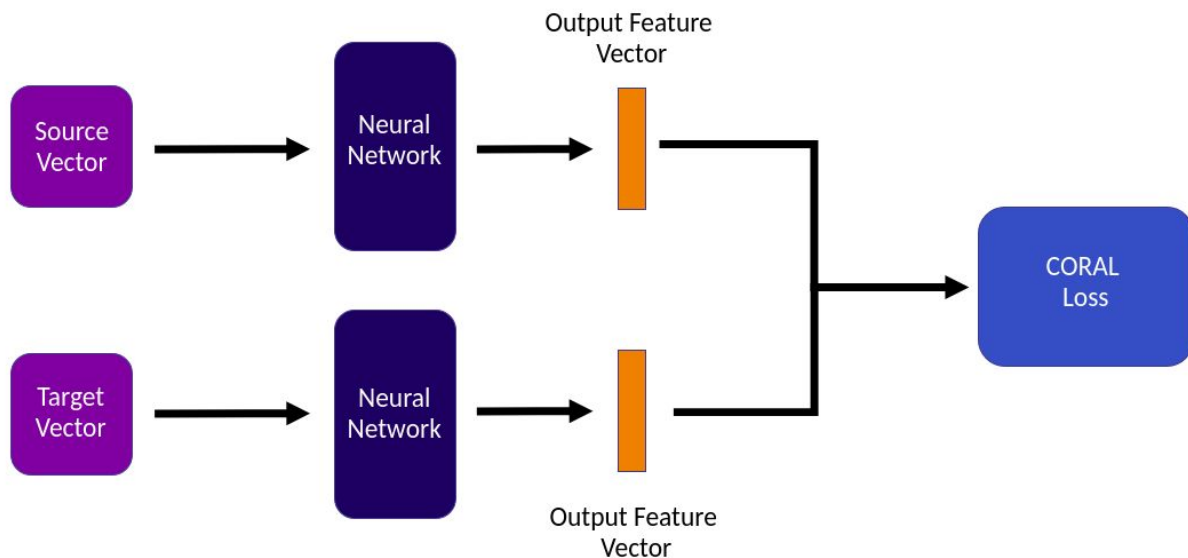


Fig. Network overview for Domain Adaptation



# Proposed Model for Correlation Alignment

- CORAL /  $\log$ CORAL Loss

$$\mathbf{C}_S = \frac{1}{n_S - 1} (\mathbf{D}_S^T \mathbf{D}_S - \frac{1}{n_S} (\mathbf{1}^T \mathbf{D}_S)^T (\mathbf{1}^T \mathbf{D}_S))$$

$$\mathbf{C}_T = \frac{1}{n_T - 1} (\mathbf{D}_T^T \mathbf{D}_T - \frac{1}{n_T} (\mathbf{1}^T \mathbf{D}_T)^T (\mathbf{1}^T \mathbf{D}_T))$$

$$L_{CORAL} = \frac{1}{4d^2} \|\mathbf{C}_S - \mathbf{C}_T\|^2$$

$$L_{\log CORAL} = \frac{1}{4d^2} \|\log(\mathbf{C}_S) - \log(\mathbf{C}_T)\|^2$$

# Proposed Model

- Combined Network

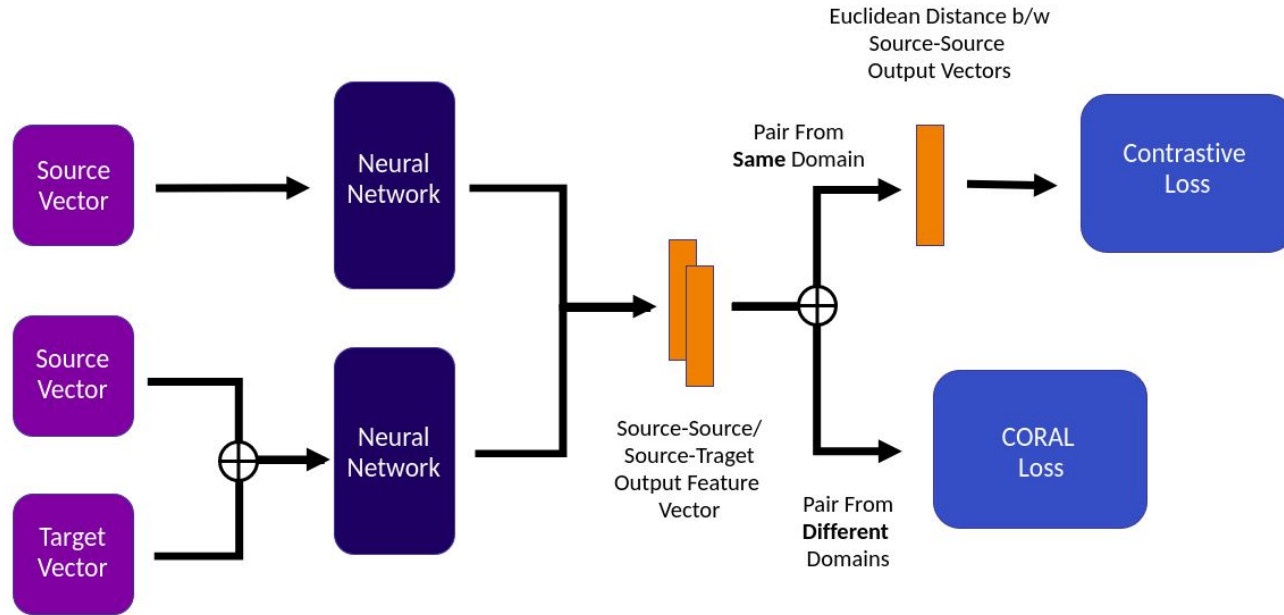


Fig. Overview of complete network

# Proposed Model

- Why perform combined training on both losses ?
- Alternate (convex) optimization

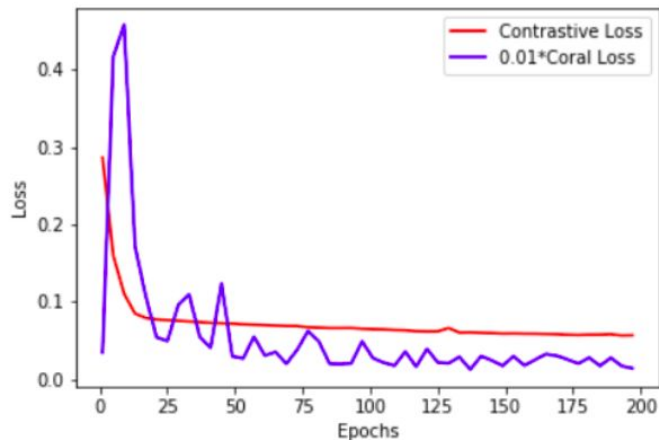


Fig. Loss curve of Contrastive loss with CORAL loss

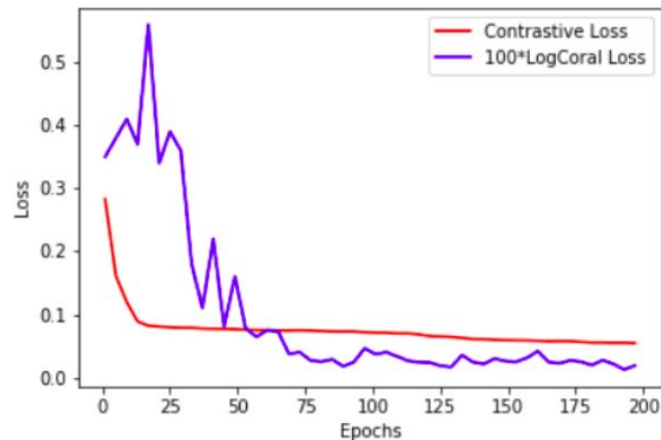


Fig. Loss curve of Contrastive loss with logCORAL loss

# Datasets

- Botswana Dataset
  - 10 spectral bands
  - 14 classes
  - Divided into 2 disjoint sets
    - Domain 1
      - TR1 (Training) : 1242
      - TS1 (Testing) : 1252
    - Domain 2
      - TR2 (Training) : 2621
      - TS2 (Testing) : 627

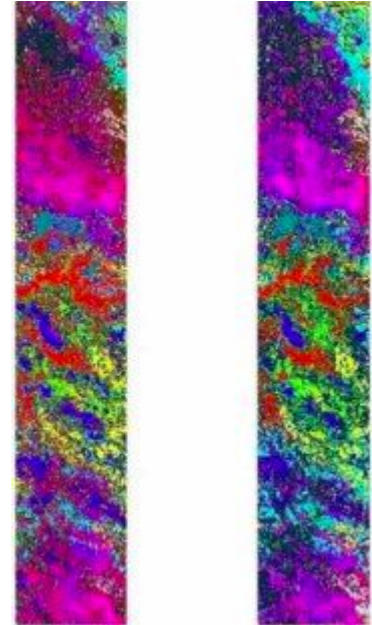
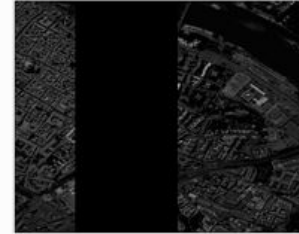


Fig. Botswana Dataset

# Datasets

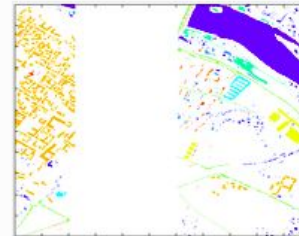
- Pavia Dataset
  - Domain 1 (Pavia Centre)
    - 102 spectral bands
    - Train : 50000
    - Test : 22933
  - Domain 2 (Pavia University)
    - 103 spectral bands
    - Train : 20000
    - Test : 19332
  - Training and Testing on 7 common classes
  - Trained and Tested on 50 features



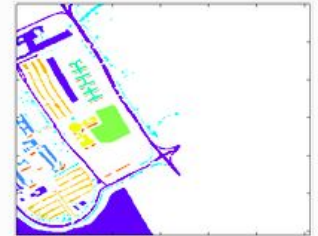
Sample band of Pavia  
Centre dataset



Sample band of Pavia  
University dataset



Groundtruth of Pavia  
Centre dataset



Groundtruth of Pavia  
University dataset

Fig. Pavia dataset with Groundtruth labels

# Results

- Botswana Dataset

Model	TR1 $\rightarrow$ TS2	TR2 $\rightarrow$ 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)	<b>76.24</b>	<b>71.09</b>

# Results

- Pavia Dataset

Model	PaviaC $\rightarrow$ PaviaU	PaviaU $\rightarrow$ PaviaC
Auto-Encoder	46.14	46.64
Deep-LogCORAL	47.57	51.28
our(CORAL)	47.72	45.86
our(LogCORAL)	<b>47.81</b>	<b>56.32</b>

# Conclusion & Future Works

- Metric learning with reduced covariance
- Metric learning based on data distribution
- Expanding our method to other standard domain adaptation datasets