Asymmetric Adaptation of Deep Features for Cross-Domain Classification in Remote Sensing Imagery

ABSTRACT

In this letter, we introduce an asymmetric adaptation neural network (AANN) method for cross-domain classification in remote sensing images. Before the adaptation process, we feed the features obtained from a pretrained convolutional neural network to a denoising autoencoder (DAE) to perform dimensionality reduction. Then the first hidden layer of AANN (placed on the top of DAE) maps the labeled source data to the target space, while the subsequent layers control the separation between the available land-cover classes. To learn its weights, the network minimizes an objective function composed of two losses related to the distance between the source and target data distributions and class separation. The results of experiments conducted on six scenarios built from three benchmark scene remote sensing data sets (i.e., Merced, KSA, and AID data sets) are reported and discussed.

EXISTING SYSTEM

- In existing system, a symmetric adaptation neural network (NN) method to reduce the shift between the distributions in a common.
- Then they optimized a cost function composed of three terms related to discrimination, distance between source and target data distributions, and geometrical structure.

PROPOSED SYSTEM

We propose an alternative approach termed as asymmetric adaptation neural network (AANN).

In a first step, we feed the CNN features extracted from the pretrained CNN into a denoising autoencoder (DAE) to perform dimensionality reduction.

The AANN (placed on the top of the DAE) is composed of two hidden fully connected layers followed by a softmax classification layer. The hidden layers use sigmoid nonlinear activation functions.

SYSTEM REQUIREMENTS

HARDWARE REQUIREMENTS:

- Processor - intel core i3
- RAM - 2GB
- Hard Disk - 20 GB

SOFTWARE REQUIREMENTS:

- Tool - MATLAB R2016
- Operating system - Windows 7,8

REFERENCE

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