Hyperspectral Image Classification with Transfer Learning

Electrical Engineering Department

Project Advisor: Birsen Sirkeci

Savaliya, Devang Kiritbhai (MS ElectricalEngineering)
Kulkarni, Shubhankar (MS Electrical Engineering)

Introduction

The primary objective is to demonstrate the effect of transfer learning between two hyperspectral datasets. Deep networks tend to overfit when the training data is limited and fail to generalize well to unseen data. To solve this problem, either more data can be collected or techniques like transfer learning must be explored. Transfer learning involves pre-training the model on a dataset with large number of labelled samples and transferring the learned weights to a target data set for better classification results. The proposed method seeks to examine whether the use of transfer learning between two hyperspectral images leads to an increase in classification accuracy over the model that was trained totally on a single dataset.

HSI Classification

The abundant spectral and spatial characteristics of materials in a hyperspectral image help in classifying hyperspectral images [1]. Due to this, the classification of hyperspectral remote sensor images plays a crucial role in applications related to urban development and resource management. Existing methods for classifying hyperspectral images have focused on exploring the spectral information only, while the spatial information is left unused. Classifying these images by only using the spectral information is difficult due to high dimensional spectra combined with limited number of samples in the training set [1]. To improve the classification performance by considering both spectral and spatial characteristics of a hyperspectral image, a 3D Residual Network (3D ResNet) was used. As the training samples are limited, the deeper network will most probably overfit and fail to generalize to unseen data. Thus, it becomes necessary to combine the use of deep residual network with techniques like transfer learning .

Dataset Description

For conducting classification experiments for classifying hyperspectral images using 3D-SRNet and transfer learning, three popular and widely used hyperspectral datasets were used. Indian Pines dataset, the Pavia University dataset and the Salinas Valley dataset. The Indian Pines dataset has images of size 145 pixels x 145 pixels with 224 spectral channels [2]. There are 16 land-cover classes in the ground truth image for the Indian Pines dataset. The Pavia University dataset has images of size 610 pixels x 340 pixels with a total of 115 spectral channels [2]. The ground truth image for the Pavia University dataset has 9 land cover classes. The Salinas Valley dataset has images of size 512 x 217 pixels with 224 spectral bands [2]. The ground truth image has 16 classes for the Salinas Valley dataset. Salinas Valley and Indian Pines datasets are captured by same sensors and their spectral and spatial characteristics are similar [2].

HSI Classification

Data pre-processing

Hyperspectral images are single images with everything in one hyperspectral cube. To work with the 3D-SRNet, small samples of size 25x25x103(spectral bands) were selected from the image and the class of central pixel in the ground truth image was the class assigned to these cubes (sample). Multiple different datasets were generated based on the overlap ratio of this small cubes. Meaning, an overlap ratio of 25% would mean, a sample belonging to a class will be selected only if next sample from same class dose not overlap more than 25% over this sample. Although, more overlap will give more data points, but it will also lead to data repeating more compared to less overlap ratio. Aim is to get better accuracy on the data generated with less overlap ratio by transfer learning.

3-D-SRNet Classification Model

A 3D-ResNet was implemented by expanding the 2D convolution layer to a 3D convolution layer. In comparison to a 2D-ResNet, a 3D-Resnet has large number of parameters. To avoid overfitting for a 3D-ResNet, the spectral components are separated from the spatial components through a separable residual (SR) unit. Figure 1 below shows the 3-D-SRNet classification model.

The 3D-SRNet is the underlying model used for training the network on a source hyperspectral dataset, this is the pretraining stage in transfer learning [1]. The pretraining stage is followed by a fine-tuning stage where the entire model is transferred except the fully connected layers to the network implemented for the target hyperspectral dataset [1]. Figure 2 shows how transfer learning is implemented. For feature extraction two SR units were implemented sequentially with hyper parameters 1e-3, 1e-5, 0.9, glorot uniform for learning rate, decay, momentum and kernel initializer for an SGD optimizer. Batch size and number of epochs were selected based on the data size. Model was implemented by modifying a ResNet available online [3].

Figure 1. Block diagram of 3-D-SRNet classification model [1]

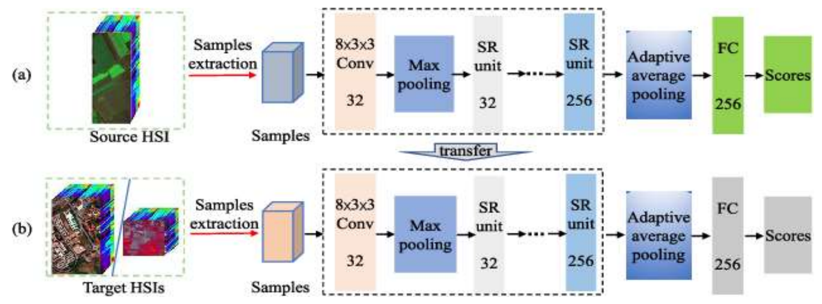

Figure 2. Block diagram of transfer learning [1]

Model generation and transfer learning

Model described in figure 1 was trained for all variations (different overlap ratios) of all three data sets. These are source models which include the classification part. To transfer only the feature extraction part, the fully connected layers were dropped before saving the model. Later these sub models can be called to predict the intermediate output which is then passed through new fully connected layers. These fully connected layers are then trained on the target data set. Figure 3 shows the block diagram of transfer learning. Here in the figure, source dataset is Salinas and target datasets are Indian pines and Pavia.

Considering all the combinations 144 models were generated (4 source model for a dataset transferred to 4 different target datasets, each dataset having 9 combinations). Table 1 below shows the accuracies of the source models. Obvious trend is seen here, as the overlap ratio increases the test accuracies are increasing. As mentioned, every possible combination of source model from this table (12 different source models) were transferred to all the variations (overlap ratios) of these three datasets and were saved. More focus is given on cases where the target dataset had the least overlap ratio (less data points) in each dataset (Salinas, Pavia and Indian pines).

Table 1. Source model test accuracies

Salinas		Pavia		Indian Pines	
Overlap Ratio	Test Accuracy	Overlap Ratio	Test Accuracy	Overlap Ratio	Test Accuracy
25%	76.4706%	25%	71.9512%	50%	40.9091%
50%	79.1209%	50%	61.5385%	75%	63.9344%
75%	88.5417%	75%	71.7105%	85%	60.3550%
95%	94.5182%	95%	84.9275%	95%	77.0701%

Results and accuracies

Expectation was to improve test accuracy for the datasets with least overlap ratio. Table 2 below shows the effect of transfer learning for combinations of source and target datasets. Table 2 also includes the transfer learning for source and target being from the same dataset. Only two of these combinations didn't show improvement in the test accuracy. All other combinations either gave the same results or were improved by transfer learning. Accuracies are highlighted based on the performance with transfer learning.

Table 2. Transfer learning test accuracies

Source model (Overlap 95%)	Target Dataset					
	Indian Pine (Overlap 50%)		Pavia (Overlap 25%)		Salinas (Overlap 25%)	
	Without transfer learning	With transfer learning	Without transfer learning	With transfer learning	Without transfer learning	With transfer learning
Indian Pines	40.9091%	63.6364%	71.9512%	71.9512%	76.4706%	70.5882%
Pavia		54.5455%		81.7073%		84.3137%
Salinas		40.9091%		54.8781%		96.0784%

Summary/Conclusions

Table 2 also shows some cases for which accuracy with transfer learning did not improve at all, an example case was for Pavia as the target dataset when source dataset was Indian pines or Salinas. For Indian pines as target, improvement can be seen with source being better model of itself or source being Pavia, and the same goes for Salinas. Source model Pavia performed comparatively better than others. This doesn't not imply that Indian pines and Salinas didn't give a good performance. It just indicates that Pavia dataset turns out to be a good source dataset. Looking at test accuracies from many other combinations which are not mentioned here, there is still some room for improvement in the way samples are selected and the way class labels are assigned.

Considering the results in table 2, this technique surely has great potential. Basic concept of transfer learning is not that hard to grasp, learning feature extraction on a similar but bigger dataset and learning information about class prediction on target dataset. Going forward this project can easily be scaled to another set of datasets with some minor changes.

Key References

1. Y. Jiang, Y. Li and H. Zhang, "Hyperspectral Image Classification Based on 3-D Separable ResNet and Transfer Learning," in IEEE Geoscience and Remote Sensing Letters.
doi: 10.1109/LGRS.2019.2913011

2. http://www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes

3. https://github.com/pantheon5100/3D-CNN-resnet-keras/blob/master/Cre_Model.py

Acknowledgement

I would like to thank Professor Birsen Sirkeci, for her support during this project and for providing all the needful resources. Her guidance at different stages during the project has helped us complete this project and also get a good understanding of different techniques involved in the project.