Lab session 1:
Land classification based on satellite images

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Abstract

In this work, we evaluate the performance of different classification strategies to determine the crop type (16 classes) of a set of pixels in a multiband spectral image. Such spectral image was taken by sensor type Airborne Visible / Infrared Imaging Spectrometer (AVIRIS) on board a satellite and it covers a region of Indiana, United States. We use different machine learning strategies, including linear, non-linear and ensemble classifiers. For the experimental implementation, we apply the cross validation technique, so that the free parameter adjustment is exclusively carried out with the data available for training. From the obtained results, we could affirm that the data present separable regions, since the Support Vector Machine (SVM) classifiers achieve a better performance than the others. To be precise, in this problem the regions seem to be separable in the form of an hyperellipsoid, because the better result is achieved with the gaussian kernel SVM.

1 Introduction

Airborne Visible / Infrared Imaging Spectrometer (AVIRIS) [1] is an optic sensor, unique in the world, that allows to obtain images of the emitted spectral radiation. It is able to measure the molecular absorption and particle scattering signatures in 224 adjacent spectral bands, with wavelengths from 400 to 2500 nanometres.

The main objective of the AVIRIS project is to identify, measure and monitor the Earth's surface and atmosphere in order to understand, monitor and predict the processes related to the global environment and the climate change. AVIRIS research areas include ecology, oceanography, geology, snow hydrology, cloud and atmospheric studies, etc [1]. In that sense, a spectral image from some crop fields from a region of Indiana (USA) is going to be used. This image was taken with the AVIRIS sensor on board a satellite, and 220 spectral bands have been used.

In this work, different types of classifiers will be used in order to catalogue the different types of crops from the spectral image.

2 Objective

The objective of this project is to carry out a comparative study of the performance of several linear, non-linear, and ensemble classifiers. They will have to be able to classify and associate the pixels from a spectral picture, taken with a satellite, of various types of crop fields. The input data will be spectral images of 145×145 pixels, which represents the molecular absorption and particle scattering signatures in 220 contiguous spectral bands. Each pixel in the image represents an area of 20 m^2. The classifiers will have to be trained so that they are able to associate the 220 spectral bands of each pixel with a type of crop field (16 classes). We will take the 20% of the labelled image pixels for training.

First of all, we normalize the preprocessed data[1] to zero mean and unit standard deviation in each of the input variables. Then, in order to carry out this project, several linear, non-linear and ensemble classifiers will be used. First, in terms of linear classifiers, the performance of the linear Support Vector Machine (SVM), Logistic Regression, and Linear Discriminant Analysis (LDA) algorithms will be studied. After that, non-linear classifiers such as K-Nearest Neighbours (K-NN), polynomial and gaussian SVM, Binary Tree, and Random Forest will be analyzed. Finally, ensemble classifiers such as Bagging and Boosting will be studied. In order to determine the optimal parameters of these classifiers, the cross-validation process will be used. And finally, a comparative analysis of the results will be made.

3 Linear classifiers

Three kinds of linear classifiers have been studied. These ones are: linear SVM, Logistic Regression, and LDA.

3.1 Linear SVM

First, we carry out the classification by means of the linear SVM algorithm, that considers the training data are linearly separable. We have performed a cross-validation (10 folds) of C (slack parameter) $\log_{10}$-spaced between –3 and 3 (10 samples), and we obtain that the optimal C is 0.46. Its corresponding testing stage error is **83.67%**.

3.2 Logistic Regression

For the case of Logistic Regression, we perform again a cross-validation (10 folds) with C $\log_{10}$-spaced between –3 and 3 (10 samples) The value selected of C is 2.15. The test accuracy of the Logistic Regression is **79.56%**.

3.3 LDA

The LDA algorithm considers that the data follow a gaussian distribution with the same covariance matrix. We have selected its default parameters. Finally, the test accuracy of LDA is **78.68%**.

3.4 Comparison

Table 1: Test accuracies for linear classifiers.

Classifier	Test accuracy
Linear SVM	83.67%
Logistic Regression	79.56%
LDA	78.68%

We can see that the best performance for linear classifiers is achieved by the linear SVM, whilst Logistic Regression and LDA present similar result. This can be because of the separability propierty of the data. Even so, the differences between the three obtained results are not so high.

4 Non-linear classifiers

Five types of non-linear classifiers have been studied. These are: K-NN, SVM with polynomial kernel, SVM with gaussian kernel, Binary Tree, and Random Forest.

4.1 K-NN

First, a K-NN classifier has been used to carry out the classification. In order to find the optimum parameter K (number of neighbours), a cross-validation process of 10 folds with values of K from 1

[1] After eliminating the pixels corresponding to the image background, and the 20 highly noisy bands that cover water absorption region.

to 21 has been performed. The optimum K-parameter obtained is 3, with a validation accuracy of 73.03% and a standard deviation of 1.35%. Once this is done, we proceed to train the classifier with the optimum K-parameter. The test accuracy obtained is **74.18%**.

4.2 SVM with polynomial kernel

Now the kernel for the SVM algorithm takes into account a polynomial decision boundary. We carry out again a cross-validation (10 folds) with C $\log_{10}$-spaced between –3 and 3 (10 samples), and the polynomial degree between 1 and 5 (5 samples). The selected value of C is 215.44, and the polynomial degree is 2. The test accuracy of the polynomial SVM is **83.46%**.

4.3 SVM with gaussian kernel

In this case, the data could be separable by means of hyperellipsoides (consequence of the gaussian distribution). We perform again a cross-validation (10 folds) with C $\log_{10}$-spaced between –3 and 3 (10 samples), and γ $\log_2$-spaced between -3 and 3 (7 samples). The selected value of C is 215.44, and the selected value of γ is $8.84{\cdot}10^{-3}$. With these validated parameters, the test accuracy of the SVM with gaussian kernel is **86.84%**.

4.4 Binary Tree

Next, we perform the classification using a binary tree. For this, the default values have been used, which means that a maximum number of depth levels of the tree has not been specified (nodes are expanded until all leaves are pure). The test accuracy obtained is **66.24%**.

4.5 Random Forest

The next classifier we have used has been the random forest classifier. In order to determine the optimal number of trees, we have performed a cross-validation process with 10 folds and with a number of trees from 1 to 10. We have repeated this process 50 times, and the average number of selected trees is 8.60, with a standard deviation of 0.57. Once this number is obtained for each of the 50 iterations, the classifier is trained, and the average test accuracy obtained for the random forest classifier is **75.14%** with a standard deviation of 0.49%.

4.6 Comparison

Table 2: Test accuracies for non-linear classifiers.

Classifier	Test accuracy
K-NN	74.18%
Polynomial kernel SVM	83.46%
Gaussian kernel SVM	86.84%
Binary Tree	66.24%
Random Forest	75.14 %

We can see the best performance is achieved by the gaussian kernel SVM method. One possible reason could be that the data are separable by means of hyperellipsoid-form decision boundaries. On the other hand, K-NN algorithm achieves the worst performance. This could be because of it does not make strong assumptions about the form of the mapping function (non-parametric algorithm). By not making assumptions, it is free to learn any functional form from the training data.

5 Ensemble classifiers

Two kinds of ensemble classifiers have been analyzed, in order to see their performance. These ones are Bagginng and Boosting.

5.1 Bagging

The first ensemble classifier is the bagging one, in which several estimators with diversity among them are build, and then their predictions are averaged.

As base learner, we used a Binary Tree with 15 depth levels. We have set the percentage of training data used to train each learner and the percentage of input features used to train each learner to 0.5. And about the number of estimators, we have studied the evolution of the bagging ensemble accuracy with the number of learners, from 1 to 50. If we use 50 learners, we obtain a test accuracy (maximum) of **75.96%**. It is noteworthy that the depth level and the percentage of training data and the input features used to train each learner could be validated, but for computing time reasons we obviated that procedure.

5.2 Boosting

The second type of ensemble classifiers we have studied is the boosting ensemble. In this case, base estimators are built sequentially forcing new learners to pay more attention to samples misclassified by previous learners.

We have tested the two types of existing Adaboost classifiers, which are the Discrete Adaboost classifier and Real Adaboost classifier. As in the previous case, we use a Binary Tree with 15 depth levels as base learner. A number of 200 estimators is selected. The test accuracy obtained of the discrete adaboost ensemble is **77.26%**. And the test accuracy obtained of the real adaboost ensemble is **76.74%**. Once again, note that the depth level and the number of estimators could be validated, but for computing time reasons we obviated that procedure.

5.3 Comparison

Table 3: Test accuracies for ensemble classifiers.

Classifier	Test accuracy
Bagging	75.96%
Discrete Adaboost	77.26%
Real Adaboost	76.74%

The best result has been obtained with the discrete adaboost ensemble. However, the obtained accuracies are very similar.

6 Conclusions

In this project we have studied the performance of several linear and non-linear classifiers in order to see which one achieves the better result. The problem consisted in cataloguing the different types of crops (16 classes) from a spectral image taken with the AVIRIS sensor on board a satellite.

We have used some linear and non-linear classifiers and we have seen that all the classifiers provide similar test accuracies. However, the binary tree classifier has slightly worse performance than the others and, on the other hand, the polynomial kernel SVM and the gaussian kernel SVM obtain better results than the rest.

Due to this result, we could affirm that the data present separable regions, since the SVM classifiers achieve a better performance than the others. To be precise, in this problem the regions seem to be separable in the form of an hyperellipsoid, because the better result is achieved with the gaussian kernel SVM.

However, the accuracies obtained from all the classifiers are very similar, and these results correspond to a fix division of the train and test samples. If we want to see which classifier has the best performance, we have to repeat the process several times in order to calculate the average and the standard deviation of the accuracy of the classifier. We have not done this because of the extremely long computational time needed. So, only with these results we cannot assure that a classifier is better than the others.

References

[1] NASA, “AVIRIS (Airborne Visible / Infrared Imaging Spectrometer).” Available: “https://aviris.jpl.nasa.gov/", 2017. [Online]. [Accessed February 28, 2017].

[2] C. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2007.

[3] R. Duda, P. Hart, and D. Stork, *Pattern Classification*. Wiley & Sons, 2nd Edition, 2000.