An assessment of various Active Learning Techniques for Classification of Remote Sensing Images

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Abstract—Efficient training set definition is one of the vital part for the success of remote sensing image classification . The intricacy of the problem, the inadequate temporal and economic resources, as well as the high intraclass variance can make an algorithm fail if suboptimal dataset is used for training. The goal of Active learning is to construct an efficient training set by iteratively improving the model performance through sampling.

Active learning, focuses on processing of data before the classification phase, found to be an active research area within the machine learning community, and is now being extensively used for remote sensing applications. Effective classification relies on the most informative pixels, at the same time the training set should be as little as possible. Active learning mechanism provide capability to select "most informative" unlabeled data and to obtain the respective labels, fulfilling both goals. Characteristics of satellite image data provide both challenges and opportunities to exploit the prospective advantages of active learning. Here an overview of active learning methods is provided, and then the latest practices proposed are assessed to cope with the problem of interactive sampling of training pixels for classification of satellite image data with support vector machines.

Keywords—Classification, Active Learning, Support Vector Machines (SVM), Margin Sampling (MS), Random Sampling(RS).

I.INTRODUCTION

For the classification of Remote Sensing Images several supervised methods have been proposed in different Remote sensing literature. In all these methods to train the classifier labeled samples are necessary, and the classification results depend on the quality of the labeled samples used for learning. However, the collection of labeled samples is time consuming and costly, and the available training samples are often not enough for an adequate learning of the classifier. Moreover, inclusion of redundant samples in the training set slows down the training step of the classifier without adding information. In order to bring down the cost of labeling, the training set should be kept as small as possible, avoiding redundant samples and including patterns which contain the largest amount of information and thus can optimize the performance of the model.

Semisupervised learning and active learning are the two popular machine learning approaches for dealing with drawbacks of supervised methods. Semisupervised algorithms incorporate the unlabeled data into the classifier training phase to obtain more precise decision boundaries. In active learning, the learning process continually queries unlabeled samples to select the most useful informative samples and updates the training set on the basis of a supervisor who attributes the labels to the selected unlabeled samples. In this way, unnecessary and redundant samples are excluded in the training set, thus significantly reducing both the labeling and computational costs. This is particularly important for remote sensing images that may have highly redundant pixels.

II.ACTIVE LEARNING

The success of remote sensing image classification depends on the definition of an efficient training set. The goal of Active learning [1], is to build efficient training sets by iteratively improving the model performance by means of sampling. Unlabeled pixels can be ranked using user-defined heuristics, according to a function of the uncertainty of their class membership and then the user is asked to provide a label for the most uncertain pixel.

A general active learner can be represented as a quintuple (*G*, *Q*, *S*, *L*, and *U*). Here *G* is a classifier, which is trained on the labeled samples in the training set *L*. *Q* being a query function used to select the most informative samples from an unlabeled sample pool *U*. *S* represents a supervisor who can assign the true class label to the selected samples from *U*. Initially, the training set *L* has few labeled samples to train the classifier *G*. Later, to select a set of samples from the unlabelled pool U, the query function *Q* is used and the supervisor *S* allots a class label to each of them. Then, these new labeled samples are included into *L*, and the classifier *G* is once again trained using the updated training set. The querying and retraining loops continue for some predefined iterations or until a stopping criterion is satisfied. *Algorithm 1* narrates a general active-learning process.

Algorithm 1: Active-learning process

Step 1: Train the classifier *G* with the training set *L* (which initially has few labeled samples).
Repeat

Step 2: Select a set of samples from the yet to be labeled pool *U* using the query function *Q*.
Step 3: Assign class label to each of the acquired samples by a supervisor S.
Step 4: Add the new labeled samples to the training set *L*.
Step 5: Retrain the classifier *G*.
Until the stop criterion is satisfied.

The query function is fundamental in the active-learning process. In [3], several methods have been proposed in the machine learning literatures which differ only in their query functions, and these different query functions are based on the evaluation of two principles(criteria): uncertainty and diversity. The uncertainty criterion is related to the confidence of the supervised algorithm in correctly classifying the considered sample, and the diversity criterion focuses on selecting a set of unlabeled samples that are as more diverse (different) as possible, which reduce the redundancy among the selected samples. The two criteria combined together results in the selection of the potentially most edifying set of samples at each iteration of the Active Learning process.

III.EASE OF USE

Different strategies have been proposed in the literature for the active selection of training examples. The MS algorithm and the active learning approaches proposed in this paper are presented in the following section.

A. Support Vector Machine (SVM)

The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output. It is assumed that a training set consists of *N* labeled samples (x_j, y_j) for j=1 to N, where $x_j \in R^d$ denotes the training samples and $y_j \in \{+1,-1\}$ denotes the associated labels (which model classes $\omega 1$ and $\omega 2$). The aim of a binary SVM is to search out a hyperplane that separates the *d*-dimensional feature space into two subspaces (one for each class).

An interesting characteristic of SVMs is related to the possibility to project the original data into a higher dimensional feature space through a kernel function *K*(., .).

The decision function *f*(*x*) is defined as,

$$f(x) = \sum_{xj \in SV} \alpha_j \, y_j \, K(x_j , q_i) + b \qquad (1)$$

here SV represents the set of support vectors. The training pattern x_j is a support vector if the corresponding α_j has a nonzero value. When a test sample q_i is given, the sign of the discriminant function $f(q_i)$ defined in [4] is used to predict its class label.

B. Margin Sampling (MS)

MS is a SVM-specific active learning algorithm taking advantage of SVM properties. Assuming a linearly separable case, when the two classes are separated by a hyperplane given by the SVM classifier [Fig.1], the support vectors are the labelled examples that lie on the margin at a distance of exactly one from the decision boundary (filled circles and diamonds in Fig.1). If we now consider an ensemble of unlabeled candidates (“X”s in Fig.1), and if the assumption is made such that the most interesting candidates are the ones that fall within the margin of the current classifier, as they are the most likely to become new support vectors [Fig.1].

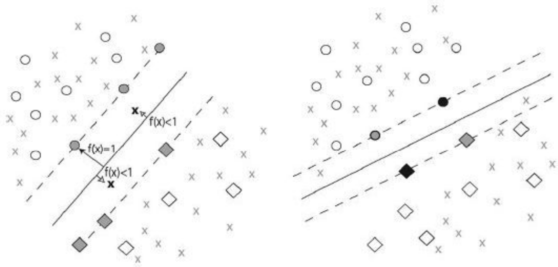


Fig.1. MS active learning. (Left) SVM before inclusion of the two most interesting examples. (Right) New SVM decision boundary after inclusion of the new training examples.

As mentioned earlier the sign of discriminate function (1) f(q_i) is used to predict its class label. In a multiclass context and using a one-against-all SVM [2], a separate classifier is trained for each class *cl* against all the others, giving a class-specific decision function *fcl*(q_i). The class attributed to the candidate *x* is the one minimizing *fcl*(q_i).

Therefore, the candidate included in the training set is the one that respects the condition

$$\hat{x} = \arg \min_{q_i \in Q} |f(qi)| \qquad (2)$$

In the case of remote sensing imagery classified with SVM, the inclusion of a single candidate per iteration is not optimal. Considering computational cost of the model (cubic with respect to the observations), inclusion of several candidates per iteration is preferable. MS provides a set of candidates at every iteration. However, MS has not been designed for this purpose, and such a straightforward adaptation of the method is not optimal on its own. The Fig. 2 shows the effect of a nonuniform distribution of candidates when several neighboring examples lie close to the margin: if the MS algorithm chooses three examples in a single run, three candidates from the same neighborhood will be chosen.

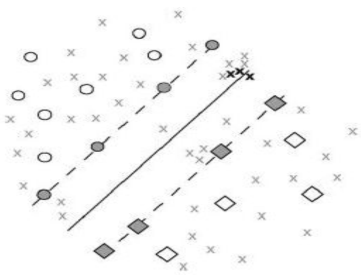


Fig. 2. MS active learning, Candidates chosen by the MS.

C. *Entropy-query-by-bagging (EQB)*

The query-by-bagging approach is quite different from the approaches discussed previously. As stated in the Introduction, the algorithm belongs to the query-by-committee algorithms, for which the choice of a candidate is based on the maximum disagreement between a committee of classifiers. In the implementation of the approach in [6], bagging is proposed to build the committee: first, *k* training sets built on bootstrap samples, i.e., a draw with replacement of the original data, are defined. Then, each set is used to train a SVM classifier and to predict the class membership of the *m* candidates. At the end of the bagging procedure, *k* possible labelings of each candidate are provided. The approach proposed in [6] has been discussed for binary classification: the candidates that will be added to the training set are the ones for which the predictions are the most evenly split, as shown in

$$x = \arg \min_{qi \in Q} \| \{t \leq k|ft(qi) = 1\} | - | \{t \leq k|ft(qi) = 0\} \| \qquad (3)$$

where t is one of the k classifiers and the binary labels are of the form $\{0, 1\}$. If the classifiers agree to a certain classification, (3) is maximized. On the contrary, uncertain candidates yield small values.

In paper [5], the heuristic of (3) is replaced by a multiclass one based on the maximum entropy of the distribution of the predictions of the k classifiers [see (5)]. By considering the k labels of a given candidate qi, it is feasible to compute the entropy of the distribution of the labels $H(qi)$ using

$$H(qi)= \qquad \Sigma \qquad (4)$$

where pi, cl is the probability to have the class cl predicted for the candidate i. $H(qi)$ is computed for each candidate in Q, and then, the candidates satisfying the heuristic

$$x = \arg\max_{qi \in Q} H(qi) \qquad (5)$$

are added to the training set.

Entropy maximization gives a naturally multiclass heuristic. A candidate for which all the classifiers in the committee agree is associated with null entropy; such a candidate is already correctly labeled by the classifiers, and its inclusion does not bring additional information. On the contrary, a candidate with maximum disagreement between the classifiers results in maximum entropy, i.e., a situation where the predictions given by the k classifiers are the most evenly split. Therefore, the parallels with the original query-by-bagging formulation are strong.

The EQB does not depend on SVM characteristics but on the distribution of k class memberships resulting from the committee learning. Therefore, it depends on the outputs of the classifiers only and can be applied to any type of classifier.

Regarding computational cost of the method, some specific considerations can be done depending on the classifier used: when using a SVM, the cost remains competitive compared to the MS presented earlier, because the training phase scales linearly with respect to the number of models k (when all the training sets are drawn in the bootstrap samples) compared to the MS using the entire training set.

IV. DATA SETS

A. *Indian Pines*

The Indian Pines scene, shown in Fig. 3(a), was collecetd by AVIRIS sensor over the Indian Pines test site in North-western Indiana and consists of 145times145 pixels and 224 spectral reflectance bands in the wavelength range 0.4–2.5 10^(-6) meters. This scene is a subset of a larger one. The Indian Pines scene consists of two-thirds agriculture, and one-third forest or other natural perennial vegetation. There are two major dual lane highways, a rail line, as well as some low density housing, other built structures, and smaller roads. Since the scene is taken in June some of the crops present, corn, soybeans, are in early stages of growth with less than 5% coverage. The groundtruth, shown in Fig. 3(b), available is designated into sixteen classes, given in TABLE I, and is not all mutually exclusive. We have also reduced the number of bands to 200 by removing bands covering the area of water absorption: [104-108], [150-163] 220.

Fig. 3(a). Sample band of Indian Pines Dataset

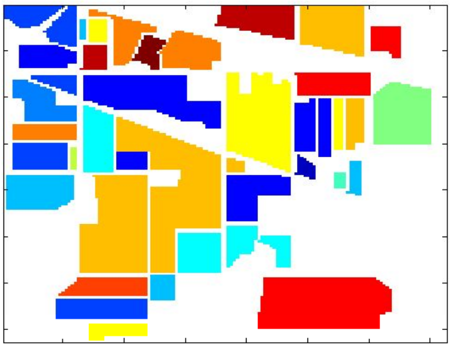


Fig. 3(b). Groundtruth of Indian Pines Dataset

TABLE I.

Ground truth classes for the Indian Pines scene and their respective samples number.

#	Class	Samples
1	Alfalfa	46
2	Corn-notill	1428
3	Corn-mintill	830
4	Corn	237
5	Grass-pasture	483
6	Grass-trees	730
7	Grass-pasture-mowed	28
8	Hay-windrowed	478
9	Oats	20
10	Soybean-notill	972
11	Soybean-mintill	2455
12	Soybean-clean	593
13	Wheat	205
14	Woods	1265
15	Buildings-Grass-Trees-Drives	386
16	Stone-Steel-Towers	93

B. *Salinas Scene*

The Salinas scene was also collected by the 224-band AVIRIS sensor over Salinas Valley, California, and is characterized by high spatial resolution (3.7-meter pixels). The area covered comprises 512 lines by 217 samples. As with Indian Pines scene, the 20 water absorption bands have been discarded, in this case bands: [108-112], [154-167], 224. This image was available only as at-sensor radiance data. It includes vegetables, bare soils, and vineyard fields. Salinas groundtruth contains 16 classes.

In this paper, a small subscene of Salinas image,shown in Fig. 4(a), denoted Salinas-A, is used. It comprises 86*83 pixels located within the same scene at [samples, lines] = [591-676, 158-240] and groundtruth, shown in Fig. 4(b), of Salinas-A includes six classes (given in TABLE II).

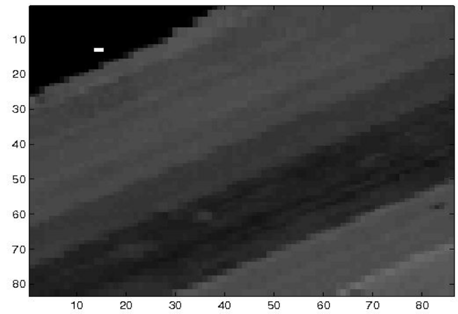


Fig. 4(a). Sample band of Salinas-A Dataset

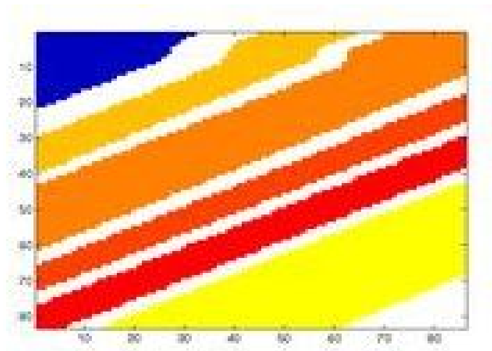


Fig. 4(b). Groundtruth of Salinas-A Dataset

TABLE II.
Ground truth classes for the Salinas-A scene and their respective samples number

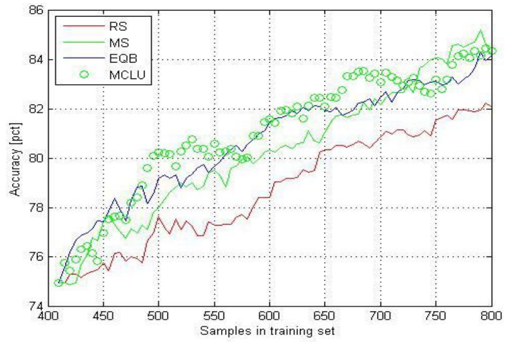
#	Class	Samples
1	Brocoli_green_weeds_1	391
2	Corn_senesced_green_weeds	1343
3	Lettuce_romaine_4wk	616
4	Lettuce_romaine_5wk	1525
5	Lettuce_romaine_6wk	674
6	Lettuce_romaine_7wk	799

V.RESULTS

In this section the different heuristics discussed are studied on the two datasets presented above. Here an effort is made to illustrate the potential of the different methods. The base learner used in the experiment is SVM classifier and the heuristics studied are: MS, MCLU, MS-ABD, MCLU-ABD and EQB. The results are compared with Random Sampling (RS).The experiments were run with 10 fold cross validation.

In Fig. 5 the result of uncertainty heuristics examined on Indian Pines dataset are compared using SVM classifiers. On Indian Pines dataset the overall performance of MCLU is better compared to other uncertainty criterions considered. The confidence value is calculated with the $c_{\text{diff}}(\mathbf{x})$ strategy for MCLU, because the effectiveness of $c_{\text{diff}}(\mathbf{x})$ uncertainty method is superior compared to $c_{\min}(x)$ strategy. The performance of MS is also close to the performance of MCLU. The reason is, in MS the candidates are ranked directly using the SVM classifier function with no further estimations. Slightly reduced performance of the EQB is due to the small size of the initial training set. In both of the experimental set up, N+5 and N+10 (shown in Fig. 5(a) and Fig. 5(b)) the performances of uncertainty methods are very similar.

In Fig. 6 with Salinas-A dataset the overall performance of MCLU is still better compared to other uncertainty criterions considered. RS is performing reasonably well, but MS does not perform well at the beginning of the learning stage. But the performance of the MS and that of EQB are closer to each other.



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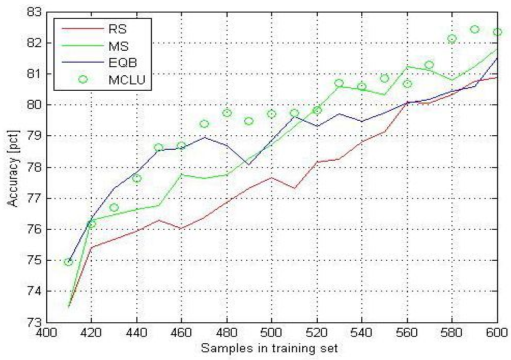
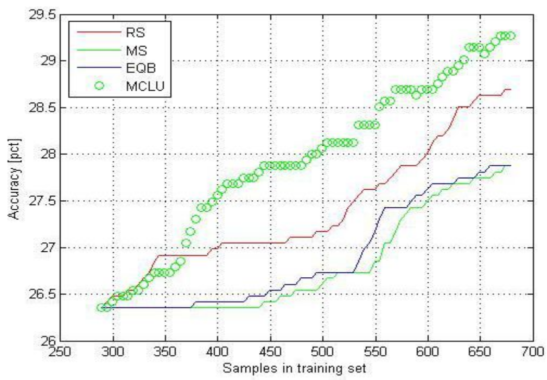
(a) N+5 pixels per iteration

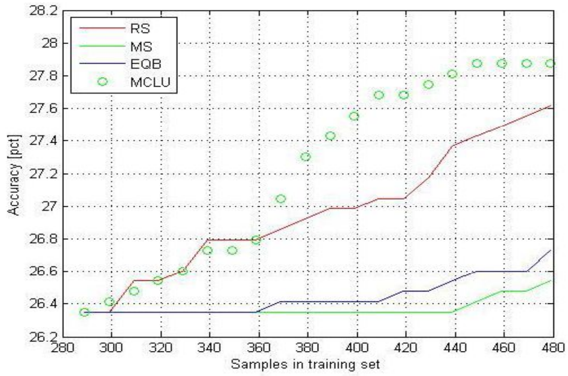


(b) N+10 pixels per iteration

Fig. 5: Result of uncertainty heuristics examined on Indian Pines dataset



(a) N+5 pixels per iteration

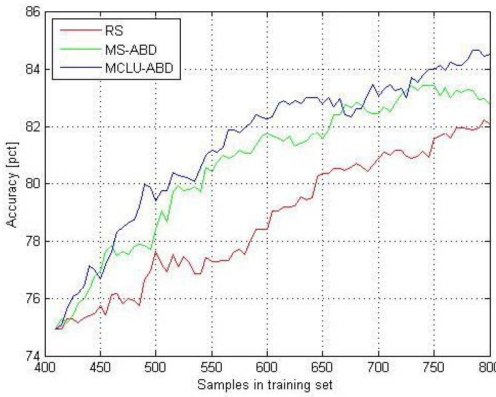


(b) N+10 pixels per iteration

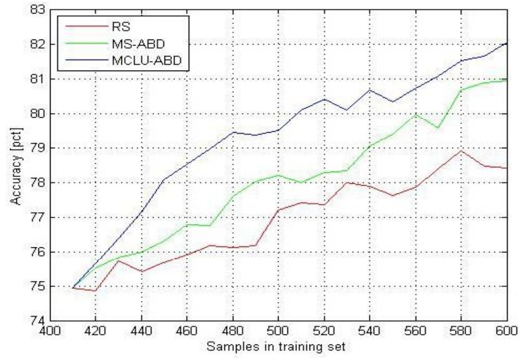
Fig. 6: Result of uncertainty heuristics examined on Salinas-A dataset

In Fig. 7 and Fig. 8 the result of the uncertainty and diversity criteria are illustrated. In Fig. 7 the result of uncertainty and diversity heuristics are examined on Indian Pines dataset. It can be observed that the effectiveness of the MCLU-ABD is better compared to MS and MCLU without considering the diversity criterion. The performance of MS-ABD is also close enough to the performance of MCLU-ABD. There exists some added computational cost involved in the improvement of the performance when diversity criterion is used.

In Fig. 8the result of uncertainty and diversity heuristics are examined on Salinas-A dataset. In the result obtained again MCLU-ABD is performing well. But MS-ABD does not perform well at the beginning of the learning stage. But as the number of training samples increases, one can observe the gradual rise in accuracy of MS-ABD, which is expected to converge with RS.

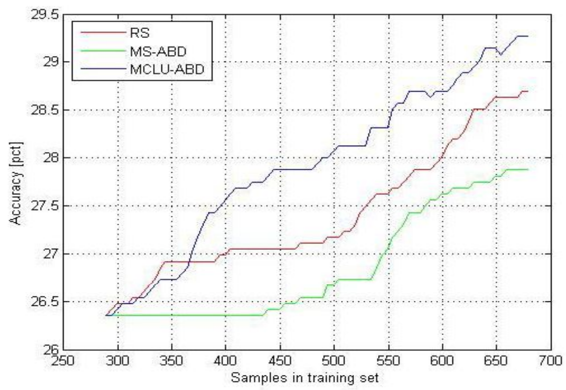


(a) N+5 pixels per iteration

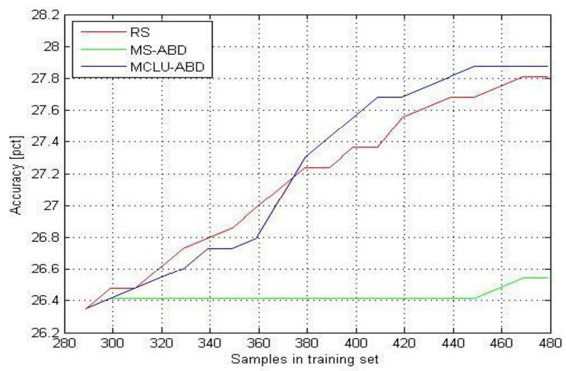


(b) N+10 pixels per iteration

Fig. 7: Result of uncertainty and diversity heuristics examined on Indian Pines dataset.



(a) N+5 pixels per iteration



(b) N+10 pixels per iteration

Fig. 8: Result of uncertainty and diversity heuristics examined on Salinas-A dataset.

IV. CONCLUSION

Here an attempt is made to study various active learning techniques for the remote sensing image classification. Margin Sampling (MS), Entropy Query by Bagging (EQB), Multiclass Level Uncertainty (MCLU), Margin Sampling-Angle Based Diversity (MS-ABD) and Multiclass Level Uncertainty-Angle Based Diversity (MCLU-ABD) algorithms have been studied and compared against random sampling. It is found that in all the cases where the combination of uncertainty and diversity are considered, MCLU-ABD is performing better than the other methods. When only uncertainty criteria is considered (absence of diversity criteria), MCLU has performed better than other methods.

Also at the regularisation or selection stage multi kernel sparse representation can be implemented and analysed for improving the performance of the classifier.

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