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# Discriminative Batch Mode Active Learning

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## Abstract

Active learning sequentially selects unlabeled instances to label with the goal of reducing the effort needed to learn a good classifier. Most previous studies in active learning have focused on selecting one unlabeled instance to label at one time while retraining in each iteration. Recently a few batch mode active learning approaches have been proposed that select a *set* of most informative unlabeled instances in each iteration under the guidance of some heuristic scores. In this paper, we propose a discriminative batch mode active learning approach that formulates the instance selection task as a continuous optimization problem over auxiliary instance selection variables. The optimization is formulated to maximize the discriminative classification performance of the target classifier, while also taking the unlabeled data into account. Although the objective is not convex, we can manipulate a quasi-Newton method to obtain a good local solution. Our empirical studies on UCI datasets show that the proposed active learning is more effective than current state-of-the-art batch mode active learning algorithms.

## 1 Introduction

Learning a good classifier requires a sufficient number of labeled training instances. In many circumstances, unlabeled instances are easy to obtain, while labeling is expensive or time consuming. For example, it is easy to download a large number of webpages, however, it typically requires manual effort to produce the labels. Randomly selecting unlabeled instances for labeling is inefficient in many situations, since non-informative or redundant instances might be selected. Aiming to reduce labeling effort, active learning (i.e., selective sampling) methods have been adopted to control the labeling process in many areas of machine learning.

Given a large pool of unlabeled instances, active learning provides a way to iteratively select the most informative unlabeled instances—the queries—from the pool to label. This is the typical setting of pool-based active learning. Most active learning approaches, however, have focused on selecting only one unlabeled instance at one time, while retraining the classifier on each iteration. When the training process is hard or time consuming, this repeated retraining is inefficient. Furthermore, if a parallel labeling system is available, a single instance selection system can make wasteful of the resource. Thus, a batch mode active learning strategy that selects multiple instances each time is more appropriate under these circumstances. Simply using a single instance selection strategy to select more than one unlabeled instance in each iteration does not work well, since it fails to take the information overlap between the multiple instances into account. Principles for batch mode active learning need to be developed to address the multi-instance selection specifically. In fact, a few batch mode active learning approaches have been proposed recently [2, 8, 9, 17, 19]. However, most extend existing single instance selection strategies into multi-instance selection simply by using a heuristic score or greedy procedure to ensure both the instance diversity and informativeness.

In this paper, we propose a new discriminative batch mode active learning method, which exploits the information contained in the unlabeled set and targets the goal of learning a good classifier

directly. We define a good classifier to be one that obtains high likelihood on the labeled training instances and low uncertainty on labels of the unlabeled instances. We therefore formulate the instance selection problem as an optimization problem with respect to auxiliary instance selection variables, taking the measure of good classification as the objective function. This optimization problem is a NP-hard problem, and it is intractable to seek the exact optimal solution. However, we can approximate it locally using the second order Taylor expansion and then obtain a suboptimal solution using a quasi-Newton local optimization technique.

The instance selection variables we introduce in the optimization in fact indicate the optimistic guesses for the labels of the selected unlabeled instances. A concern about our discriminative instance selection therefore is that some information in the unlabeled data not consistent with the true classification partition might mislead the instance selection process. Fortunately, our active learning method can immediately tell whether it has been misled by comparing the true labels to its prior guesses. We can adjust the active selection strategy in the next iteration whenever a mismatch between the labeled and unlabeled data is detected. An empirical study on UCI datasets shows that our new batch mode active learning method is more effective than some current state-of-the-art batch mode active learning algorithms.

## 2 Related Work

Many researchers have addressed the active learning problem in various ways. Most have focused on selecting a single most informative unlabeled instance to label each time. Many such approaches make myopic decisions based solely on the current learned classifiers and select the unlabeled instance they are most uncertain about to label. [10] chooses the unlabeled instance with conditional probability closest to 0.5 as the most uncertain instance. [5] takes the instance on which a committee of classifiers disagree the most. [3, 18] suggest choosing the instance closest to the classification boundary, and [18] analyzes this active learning as a version space reduction process. Approaches making use of unlabeled data to provide complementary information for active learning have also been proposed. [4, 20] employ the unlabeled data by using the prior density  $p(\mathbf{x})$  as uncertainty weights. [16] selects instance that optimizes the expected generalization error over the unlabeled data. [11] uses an EM approach to integrate the information from unlabeled data. [13, 22] consider combining active learning with semi-supervised learning. [14] presents a mathematical model that explicitly combines clustering and active learning. [7] presents a discriminative active learning approach, which implicitly exploits the clustering information contained in the unlabeled data in an optimistic way.

Since single instance selection strategies require tedious retraining with each single instance being labeled (and they can not take advantages of parallel labeling systems), many batch mode active learning methods have been proposed recently. [2, 17, 19] extend single instance selection strategies that use support vector machines. [2] takes the diversity of the selected instances into account, in addition to individual informativeness. [19] proposes a representative sampling approach that selects the cluster centers of the instances lying within the margin of the support vector machine. [8, 9] choose multiple instances that efficiently reduce the Fisher information. Overall, these approaches use various heuristics to guide the instances selection such that the selected batch should be informative about the classification model, while being diverse enough so that their information overlap would be minimized.

Instead of using heuristic measures, in this paper, we formulate batch mode active learning as an optimization problem that aims to learn a good classifier directly. Our optimization selects the best set of unlabeled instances and their labels to produce a classifier that attains maximum likelihood on labels of the labeled instances while attaining minimum uncertainty on labels of the unlabeled instances. It is apparently intractable to do an exhaustive search for the optimal solution; our optimization problem is NP-hard. Nevertheless we can exploit a second-order Taylor approximation and use a quasi-Newton optimization method to quickly reach a local solution. Optimization techniques have been widely used in machine learning research. [1] provides an examination on the interaction of machine learning and mathematical programming. Our proposed approach provides an example of exploiting optimization techniques in the batch model active learning research.

### 3 Logistic Regression

In this paper, we use binary logistic regression as our base classification algorithm. Logistic regression is a well-known and mature statistical model for probabilistic classification that has been actively studied and applied in machine learning. Given a test instance  $\mathbf{x}$ , binary logistic regression models the conditional probability of the class label  $y \in \{+1, -1\}$

$$p(y = \pm 1 | \mathbf{x}, \mathbf{w}) = \frac{1}{1 + \exp(-y\mathbf{w}^\top \mathbf{x})}$$

where  $\mathbf{w}$  is the model parameter. Here the bias term is omitted for simplicity of notation. The model parameters can be trained by maximizing the likelihood of the labeled training data, i.e., minimizing the logloss of the training instances

$$\min_{\mathbf{w}} \sum_{i \in L} \log(1 + \exp(-y_i \mathbf{w}^\top \mathbf{x}_i)) + \frac{\lambda}{2} \mathbf{w}^\top \mathbf{w} \quad (1)$$

where  $L$  indexes the training instances and  $\frac{\lambda}{2} \mathbf{w}^\top \mathbf{w}$  is a regularization term introduced to avoid overfitting problems. Logistic regression is a robust classifier that can be trained efficiently using various convex optimization techniques [12]. It is also a linear classifier, however it is easy to obtain nonlinear classifications by simply introducing kernels [21].

### 4 Discriminative Batch Mode Active Learning

During the process of active learning, there will typically be a small number of labeled instances relative to a large number of unlabeled instances. Instance selection strategies based only on the labeled data therefore ignore potentially useful information contained in the unlabeled instances. In this section, we present a new discriminative batch mode active learning algorithm for binary classification, which exploits the information in the unlabeled instances. Our approach is *discriminative* because: (1) it selects a batch of instances through optimizing a discriminative classification model; (2) it selects the instances by considering the best discriminative configuration of their labels that leads to the best classifier. Unlike other batch mode active learning approaches, which identify the most informative batch of instances using heuristic measures, our approach aims to identify the batch of instances that directly optimizes classification performance.

#### 4.1 Optimization Problem

The optimal active learning strategy is to select the set of instances to label that leads to learning the best classifier. Supervised learning methods typically maximize the likelihood of training instances to obtain a good classifier. With the unlabeled data being available, some semi-supervised learning method that performs training by maximizing the likelihood of labeled instances and minimizing the uncertainty of the labels for unlabeled instances has been proposed to achieve a classifier with better generalization performance [6]. That is to obtain a good classifier by maximizing the expected log likelihood of the labeled and unlabeled data

$$\sum_{i \in L} \log P(y_i | \mathbf{x}_i, \mathbf{w}) + \alpha \sum_{j \in U} \sum_{y = \pm 1} P(y | \mathbf{x}_j, \mathbf{w}) \log P(y | \mathbf{x}_j, \mathbf{w}) \quad (2)$$

where  $\alpha$  is a tradeoff parameter used to adjust the relative influence of the labeled and unlabeled data;  $\mathbf{w}$  specifies the conditional model;  $L$  indexes the labeled instances, and  $U$  indexes the unlabeled instances.

Our new active learning approach is motivated by this semi-supervised learning principle. We propose to select a batch of unlabeled instances  $S$  from  $U$  to label in each iteration, with the goal of maximizing the objective (2). Specifically, we define the score function for a set of selected instances  $S$  in the iteration  $t + 1$  as below

$$f(S) = \sum_{i \in L^t \cup S} \log P(y_i | \mathbf{x}_i, \mathbf{w}^{t+1}) - \alpha \sum_{j \in U^t \setminus S} H(y | \mathbf{x}_j, \mathbf{w}^{t+1}) \quad (3)$$

where  $\mathbf{w}^{t+1}$  is the parameter set for the conditional classification model trained on the new labeled set  $L^{t+1} = L^t \cup S$ , and  $H(y|\mathbf{x}_j, \mathbf{w}^{t+1})$  denotes the entropy of the conditional distribution  $P(y|\mathbf{x}_j, \mathbf{w}^{t+1})$ , such that

$$H(y|\mathbf{x}_j, \mathbf{w}^{t+1}) = - \sum_{y=\pm 1} P(y|\mathbf{x}_j, \mathbf{w}^{t+1}) \log P(y|\mathbf{x}_j, \mathbf{w}^{t+1})$$

Our active learning strategy is to select the batch of instances that has the highest score.

In practice, however it is problematic to use the  $f(S)$  score guiding the instance selection: we do not know the labels for instances  $S$  when the selection is conducted. One typical solution for this problem is to use the expected  $f(S)$  score computed under the current conditional model specified by  $\mathbf{w}^t$

$$\mathbf{E}[f(S)] = \sum_{\mathbf{y}_S} P(\mathbf{y}_S|\mathbf{x}_S, \mathbf{w}^t) f(S)$$

However, using  $P(\mathbf{y}_S|\mathbf{x}_S, \mathbf{w}^t)$  as weights, this expectation might aggravate the ambiguity that already exists in the current classification model  $\mathbf{w}^t$ , which has been trained on a very small labeled set  $L^t$ . Here, we propose an optimistic solution instead: use the best  $f(S)$  score that the batch of unlabeled instances  $S$  can achieve with their all possible label configurations. This optimistic scoring function can be written as

$$f(S) = \max_{\mathbf{y}_S} \sum_{i \in L^t \cup S} \log P(y_i|\mathbf{x}_i, \mathbf{w}^{t+1}) - \alpha \sum_{j \in U^t \setminus S} H(y|\mathbf{x}_j, \mathbf{w}^{t+1}) \quad (4)$$

Thus the problem becomes how to select a set of instances  $S$  that achieves the best optimistic  $f(S)$  score defined in (4). Although this problem can be solved using an exhaustive search on all  $m = |S|$  subsets of the unlabeled set  $U$ , it is intractable to do so in practice, since the search space is exponentially large. Explicit heuristic search approaches seeking a local optima do not exist either, since it is hard to define an efficient set of systematic operations that can transfer from one position to another one within the search space while guaranteeing improvements over the optimistic score.

In this paper, we propose to approach optimistic batch mode active learning by formulating the problem as an explicit mathematical optimization. Given the labeled set  $L^t$  and unlabeled set  $U^t$  after iteration  $t$ , the task in the iteration  $t + 1$  is to select a subset  $S$  from  $U^t$  that achieves the best score defined in (4). We first introduce a set of instance selection variables  $\boldsymbol{\mu}$ , which is a  $\{0, 1\}$ -valued,  $|U^t| \times 2$  sized indicator matrix, and each row vector  $\boldsymbol{\mu}_j$  corresponds to the two labels  $\{+1, -1\}$  of the  $j$ th instance in  $U^t$ . Then the optimistic instance selection for iteration  $t + 1$  can be formulated as the following optimization problem

$$\max_{\boldsymbol{\mu}} \sum_{i \in L^t} \log P(y_i|\mathbf{x}_i, \mathbf{w}^{t+1}) + \beta \sum_{j \in U^t} \mathbf{v}_j^{t+1} \boldsymbol{\mu}_j^\top - \alpha \sum_{j \in U^t} (1 - \boldsymbol{\mu}_j \mathbf{e}) H(y|\mathbf{x}_j, \mathbf{w}^{t+1}) \quad (5)$$

$$s.t. \quad \boldsymbol{\mu} \in \{0, 1\}^{|U^t| \times 2}; \quad (6)$$

$$\langle \boldsymbol{\mu}, \mathbf{E} \rangle = m; \quad (7)$$

$$\boldsymbol{\mu}_j \mathbf{e} \leq 1, \forall j; \quad (8)$$

$$\mathbf{1}^\top \boldsymbol{\mu} \leq \left(\frac{1}{2} + \epsilon\right) m \mathbf{e}^\top \quad (9)$$

where  $\mathbf{v}_j^{t+1}$  is a row vector  $[\log P(y = 1|\mathbf{x}_j, \mathbf{w}^{t+1}), \log P(y = -1|\mathbf{x}_j, \mathbf{w}^{t+1})]$ ;  $\mathbf{e}$  is a 2-entry column vector with all 1s;  $\mathbf{1}$  is a  $|U^t|$ -entry column vector with all 1s;  $\mathbf{E}$  is a  $U^t \times 2$  sized matrix with all 1s;  $\epsilon$  is a user-provided parameter controlling the class balance for the instance selection; and  $\beta$  is a parameter we will use later to adjust our belief in the guessed labels. Note that, the selection variables  $\boldsymbol{\mu}$  not only choose instances from  $U^t$ , but also select labels for the selected instances. Solving this optimization yields the optimal  $\boldsymbol{\mu}$  for instance selection in iteration  $t + 1$ .

The optimization (5) is an integer programming problem that produces equivalent results to using exhaustive search to optimize (4), except that we have additional class balance constraints (9) here. Integer programming is an NP-hard problem. The first step we made for solving this problem is to relax it into a continuous optimization by replacing the integer constraints (6) with continuous

constraints  $0 \leq \boldsymbol{\mu} \leq 1$

$$\max_{\boldsymbol{\mu}} \quad \sum_{i \in L^t} \log P(y_i | \mathbf{x}_i, \mathbf{w}^{t+1}) + \beta \sum_{j \in U^t} \mathbf{v}_j^{t+1} \boldsymbol{\mu}_j^\top - \alpha \sum_{j \in U^t} (1 - \boldsymbol{\mu}_j \mathbf{e}) H(y | \mathbf{x}_j, \mathbf{w}^{t+1}) \quad (10)$$

$$s.t. \quad 0 \leq \boldsymbol{\mu} \leq 1; \quad (11)$$

$$\langle \boldsymbol{\mu}, \mathbf{E} \rangle = m; \quad (12)$$

$$\boldsymbol{\mu}_j \mathbf{e} \leq 1, \forall j; \quad (13)$$

$$\mathbf{1}^\top \boldsymbol{\mu} \leq \left(\frac{1}{2} + \epsilon\right) m \mathbf{e}^\top \quad (14)$$

If we can solve this continuous optimization problem, a greedy strategy can then be used to recover the integer solution by iteratively setting the largest non-integer  $\boldsymbol{\mu}$  value to 1 with respect to the constraints. However, this relaxed optimization problem is still very complex, and its objective function (10) can be viewed as an arbitrary function of  $\boldsymbol{\mu}^1$  and therefore non-concave. Nevertheless, standard continuous optimization techniques can be used to solve for a local maxima.

## 4.2 Quasi-Newton Method

The objective function (10) is a function of the instance selection variables  $\boldsymbol{\mu}$

$$f(\boldsymbol{\mu}) = \sum_{i \in L^t} \log P(y_i | \mathbf{x}_i, \mathbf{w}^{t+1}) + \beta \sum_{j \in U^t} \mathbf{v}_j^{t+1} \boldsymbol{\mu}_j^\top - \alpha \sum_{j \in U^t} (1 - \boldsymbol{\mu}_j \mathbf{e}) H(y | \mathbf{x}_j, \mathbf{w}^{t+1}) \quad (15)$$

However, this function is non-concave, and convenient convex optimization techniques that achieve global optimal solutions cannot be applied. Nevertheless, we develop a local optimization approach that exploits a variant of quasi-Newton method to quickly determine a local optimal solution  $\boldsymbol{\mu}^*$ . The local optimization approach iteratively updates  $\boldsymbol{\mu}$  to improve the objective (15), and stops when a local maxima is reached. At each iteration, it makes a local move that allows it to achieve the largest improvement in the objective function, along the direction decided by cumulative information obtained from the sequence of local gradients. Suppose  $\bar{\boldsymbol{\mu}}_{(k)}$  is the starting point for iteration  $k$ . We first derive a second-order Taylor approximation  $\tilde{f}(\boldsymbol{\mu})$  for the objective function  $f(\boldsymbol{\mu})$  at  $\bar{\boldsymbol{\mu}}_{(k)}$

$$\tilde{f}(\boldsymbol{\mu}) = f(\bar{\boldsymbol{\mu}}_{(k)}) + \nabla f_k^\top \text{vec}(\boldsymbol{\mu} - \bar{\boldsymbol{\mu}}_{(k)}) + \frac{1}{2} \text{vec}(\boldsymbol{\mu} - \bar{\boldsymbol{\mu}}_{(k)})^\top H_k \text{vec}(\boldsymbol{\mu} - \bar{\boldsymbol{\mu}}_{(k)}) \quad (16)$$

where  $\text{vec}(\cdot)$  is a function that transforms a matrix into a column vector;  $\nabla f_k = \nabla f(\bar{\boldsymbol{\mu}}_{(k)})$  and  $H_k$  denote the gradient vector and Hessian matrix of  $f(\boldsymbol{\mu})$  at point  $\bar{\boldsymbol{\mu}}_{(k)}$  respectively. Since our original optimization function  $f(\boldsymbol{\mu})$  is smooth, the quadratic function  $\tilde{f}(\boldsymbol{\mu})$  can reasonably approximate it in a small neighborhood of  $\bar{\boldsymbol{\mu}}_{(k)}$ . Thus we can determine our update direction by solving a quadratic programming with the objective (16) and linear constraints (11), (12), (13) and (14). Suppose the optimal solution for this quadratic program is  $\tilde{\boldsymbol{\mu}}_{(k)}^*$ , a reasonable update direction  $\mathbf{d}_k = \tilde{\boldsymbol{\mu}}_{(k)}^* - \bar{\boldsymbol{\mu}}_{(k)}$  can then be obtained for iteration  $k$ . Given this direction, a back-track line search can be used to guarantee improvement over the original objective (15). Note that for each different value of  $\boldsymbol{\mu}$ ,  $\mathbf{w}^{t+1}$  has to be retrained on  $L^t \cup S$  to evaluate the new objective value, since  $S$  is determined by  $\boldsymbol{\mu}$ . In order to reduce the computational cost, we approximate the training of  $\mathbf{w}^{t+1}$  in our empirical study, by limiting it to a few Newton-steps with a starting point given by  $\mathbf{w}^t$  trained only on  $L^t$ .

The remaining issue is to compute the local gradient  $\nabla f(\bar{\boldsymbol{\mu}}_{(k)})$  and the Hessian matrix  $H_k$ . We assume  $\mathbf{w}^{t+1}$  remains constant with small local updates on  $\bar{\boldsymbol{\mu}}$ . Thus the local gradient can be approximated as

$$\nabla f(\bar{\boldsymbol{\mu}}_{j(k)}) = \beta \mathbf{v}_j^{t+1} + \alpha [H(y | \mathbf{x}_j, \mathbf{w}^{t+1}), H(y | \mathbf{x}_j, \mathbf{w}^{t+1})]$$

$\nabla f(\bar{\boldsymbol{\mu}}_{(k)})$  can be constructed from all  $\nabla f(\bar{\boldsymbol{\mu}}_{j(k)})$ . We then use BFGS (Broyden-Fletcher-Goldfarb-Shanno) to compute the Hessian matrix, which starts as an identity matrix for the first iteration, and is updated in each iteration as follows [15]

$$H_{k+1} = H_k - \frac{H_k s_k s_k^\top H_k}{s_k^\top H_k s_k} + \frac{y_k y_k^\top}{y_k^\top s_k}$$

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<sup>1</sup>Note that  $\mathbf{w}^{t+1}$  is the classification model parameter set trained on  $L^{t+1} = L^t \cup S$ , where  $S$  indexes the unlabeled instances selected by  $\boldsymbol{\mu}$ . Therefore  $\mathbf{w}^{t+1}$  is a function of  $\boldsymbol{\mu}$ .

where  $y_k = \nabla f_{k+1} - \nabla f_k$ , and  $s_k = \bar{\mu}_{(k+1)} - \bar{\mu}_{(k)}$ . This Hessian matrix accumulates information from the sequences of local gradients to help determine better update directions.

### 4.3 Adjustment Strategy

In the discriminative optimization problem we formulated in Section 4.1, the  $\mu$  variables are used to optimistically select both instances and their labels, aiming to achieve the best classification model according to the objective (5). When the labeled set is small, and the discriminative partition (clustering) information contained in the large unlabeled set is not consistent with the true classification, the labels optimistically *guessed* for the selected instances through  $\mu$  might not be consistent with the true labels either. Thus, the instance selected will not be very useful for identifying our true classification model. Furthermore, the unlabeled data might continue to mislead the next instance selection iteration.

Fortunately, we can immediately identify this problem of being misled after obtaining the true labels for the selected instances. If the true labels are different from the guessed labels that are returned by the optimization problem, we need to make some adjustment for the next instance selection iteration. We have tried a few adjustment strategies in our study. We report the most effective one in this paper. Note that the *being-misled* problem is in fact caused by the unlabeled data that affects the target classification model through the term  $\beta \sum_{j \in U^t} \mathbf{v}_j^{t+1} \mu_j^\top$ . Therefore, a simple way to fix the problem is to adjust the parameter  $\beta$ . Specifically, at the end of each iteration  $t$ , we obtain the true labels  $\mathbf{y}_S$  for the selected instances  $S$ , and compare them with our guessed labels  $\hat{\mathbf{y}}_S$  indicated by  $\mu^*$ . If they are consistent, we will set  $\beta = 1$ , which means we trust the partition information from the unlabeled data as same as the label information in the labeled data for building the classification model. If  $\mathbf{y}_S \neq \hat{\mathbf{y}}_S$ , apparently we should reduce the  $\beta$  value, that is, reducing the influence of the unlabeled data for the next selection iteration  $t+1$ . We use a simple heuristic procedure to determine the  $\beta$  value in this case. Starting from  $\beta = 1$ , we then iteratively reduce its value by a small factor 0.5, until a better objective value for (15) can be obtained when replacing the guessed indication variables  $\mu^*$  with the true labeling indications. Note that, if we reduce  $\beta$  to zero, our optimization problem will be exactly equivalent to picking the most uncertain instance when  $m = 1$ .

## 5 Experiments

To investigate the empirical performance of our discriminative batch mode active learning algorithm, we conducted a set of experiments on nine two-class UCI datasets, comparing with a baseline random instance selection algorithm, a non-batch myopic active learning method that selects the most uncertain instance each time, and two batch mode active learning methods proposed in the literature: *svmD*, an approach that incorporates diversity in active learning with SVM [2]; *Fisher*, an approach that uses Fisher information matrix for instance selection [9]. The UCI datasets we used include (we show the name, followed by the number of instances and the number of attributes): Australian(690;14), Cleve(303;13), Corral(128;6), Crx(690;15), Flare(1066;10), Glass2(163;9), Heart(270;13), Hepatitis(155;20) and Vote(435;15).

We consider a hard case of active learning, where we start active learning from only a few labeled instances. In each experiment, we start with four randomly selected labeled instances, two in each class. We then randomly select 2/3 of the remaining instances as the unlabeled set, using the remaining instances for testing. All the algorithms start with the same initial labeled set, unlabeled set and testing set. For a fixed batch size  $n$ , each algorithm repeatedly select  $n$  instances to label each time. In this section, we report the experimental results with  $n = 5$ , averaged over 20 times repetitions.

Figure 1 shows the comparison results on the nine UCI datasets. These results suggest that although the baseline random sampling method works surprisingly well in our experiments, our proposed algorithm always performs better than it or at least achieves a comparable performance. Moreover, our proposed discriminative batch mode algorithm apparently overperforms the other two batch mode algorithms on five datasets—Australian, Cleve, Flare, Heart and Hepatitis, and reaches a tie on two datasets—Crx and Vote. The myopic most uncertain instance selection method shows an overall inferior performance to our proposed batch mode approach on Australian, Cleve, Crx, Heart and Hepatitis, and achieves a tie on Flare and Vote. However, our discriminative batch mode active learning presents an overall inferior performance over two datasets—Corral and Glass2, where the

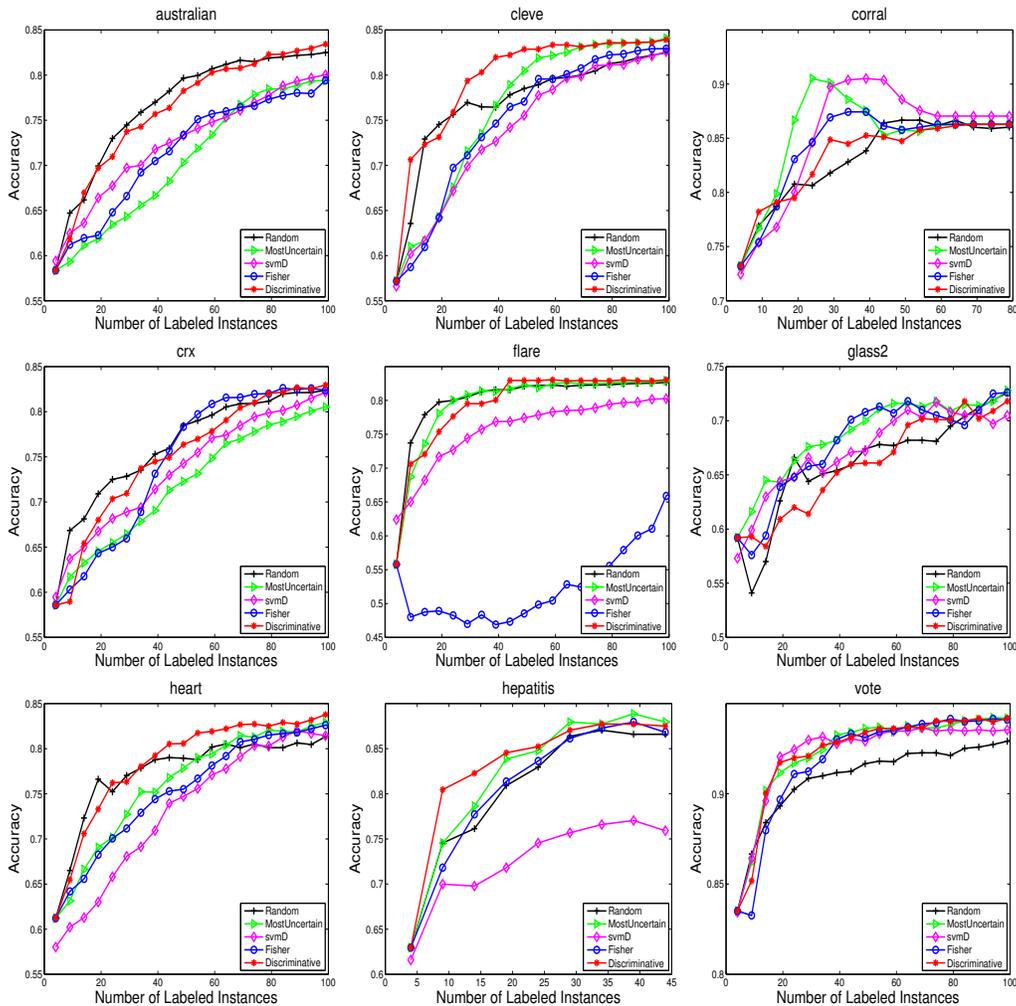


Figure 1: Results on UCI Datasets

evaluation lines for most algorithms in the figures are strangely very bumpy. The reason behind this remains to be investigated.

These empirical results suggest that selecting unlabeled instances through optimizing the classification model directly would obtain more relevant and informative instances, comparing with using heuristic scores to guide the selection. Although the original optimization problem formulated is NP-hard, a relaxed local optimization method that leads to a local optimal solution still works effectively.

## 6 Conclusion

In this paper, we proposed a discriminative batch mode active learning approach, which exploits the information contained in the unlabeled set and selects a batch of instances through optimizing the target classification model. Although it could be overly optimistic about the information presented by the unlabeled set and cause the problem of being misled. The being-misled problem can be identified immediately after obtaining the true labels. A simple adjustment strategy can then be used to mitigate the problem in the following iteration. The experimental results on the UCI datasets show that this approach is overall more effective comparing with other batch mode active learning methods, a random sampling method and a myopic non-batch mode active learning method. Our current work is focused on 2-class classification problems, however, it is easy to be extended to multiclass classification problems.

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