AdaBoost and SVM's for Unbalanced Data Sets

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***Abstract*—Support vector machines were investigated for there use in single class and multi-class classification problems. The radial basis function was used as the kernal for, and the classifiers where trained for a variety of kernal size and regularization paramater in order to find the optimal classifier parameters for a single data set. After the optimal value were found for a single classifier the AdaBoostM1 algorthim was implemented and an ensamble of weak learners was trained. The ensamble classifier trained with AdaBoostM1 had a higher accuracy than the single support vector machine for the Glass and Liver data set. The vowel data set, however, had a very high accuracy (96%) for the single classifier while the ensamble classifiers preformed poorly. As the vowel data set was the only example of a balanced data set while the other's were unbalanced data sets, it can be concluded that the AdaBoostM1 algorthim improves the performance of a classifier on an unbalanced data set.**

I. Introduction

A supervised machine learning problem is one which a learning algorthim is presented a set of training data and attempts to find an unkown function which maps the training values to the correct answer. Typically the training set, denoted S, is a set of the form $\{(\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots, (\vec{x}_n, y_n)\}$ where $\vec{x}_i$ is vector of some features of the problem. Examples of problem features include discrete or real valued items such as height, weight, age, zip code, grade point average, starting salary, and telephone number (as just a few) which might make up the features of a person. The y_i are the class of the training feature $\vec{x}_i$ belongs to; these might be University of Tennessee students or Carnegie Mellon students. In this examples students with a zip code of 15213 are likely to be Tartans, while students with a zip code of 37916 are like to be Volunteers. The challenge arises from examples have overlaping features; for example this author as a former Tartan and current Vol would be difficult to classify by zip code. The learning algorthims job is then to find a hypothesis h that corrrectly classifies a student as a Volunteer of Tartan based on the features providied. This learning process can then be defined as finding the hypothesis that has the least error (incorrect classifications) on the training data set while extending to examples outside of the training space.

A. Support Vector Machines

Support Vector Machines (SVM) are a supervised learning technqiue in which hyperplanes are constructed in a high dimensional space to which the features are mactched. SVMs find the hyperplanes that are the farthest away from all of mapped features in order to provide excellent training performance while still maintaing the ability to generalize to new instances; i.e. SVMs are maximal margin classifiers. For a binary classification the decision function of the SVM is the dot product of the weight vector and the training example in the feature space added to a bias vector as shown in Equation 1.

$$f(\vec{x}) = \langle \vec{w}\phi(\vec{x}) \rangle + \vec{b} \tag{1}$$

where $\phi(\vec{x})$ is a mapping to the higher dimensional space. The SVM is then learning the optimal values of the weight vector $\vec{w}$ and the basis $\vec{b}$.

The radial basis function (Equation 2) is a common kernal function used to map the input vector $\vec{x}$ into a higher dimension.

$$k(\vec{x}_i, \vec{x}_j) = exp\left(-\frac{\|\vec{x}_i - \vec{x}_j\|}{2\sigma^2}\right) \tag{2}$$

The maximal margin is ensured by minimizing:

$$g(\vec{w}, \eta) = \frac{1}{2}\|\vec{w}\| + C\sum_{i=1}^{N}\zeta_i \tag{3}$$

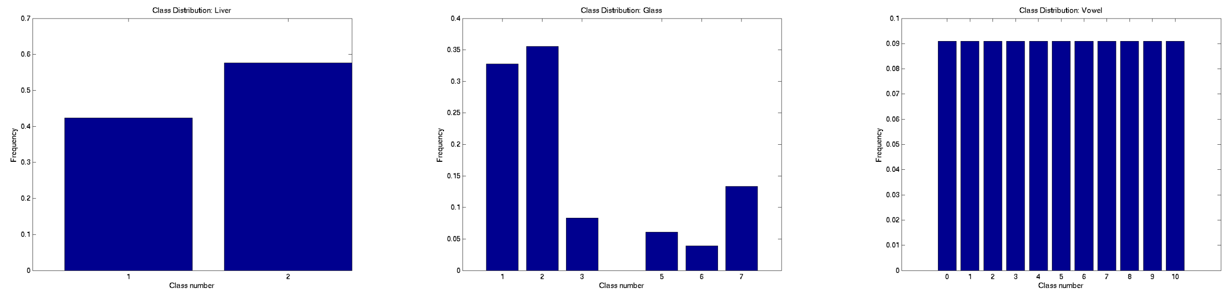
subject to:

$$y_i(\langle \vec{w}, \phi(\vec{x}) \rangle + b) \geq 1 - \zeta_i, \quad \zeta_i \geq 0 \tag{4}$$

where ζ_i is the ith slack varaible and C is the regulariazation parameter [1]. This problem can be translated in to the Wolfe dual form, which can be solved with quadratic programing [1].

B. Boosting

Unbalanced data sets (data sets in which a majority of the values come from one class, see Figure 1) are difficult for classification schemes to learn because the minority class is not well represented and tends to be thought as noise for the classifer. Often classifiers are trained from unblananced data sets by artifically reblaning the dataset by sampling techniques; i.e. up-sampling (sampling more from the minoarty class) and down-sampling (sampling less from the majoirty class). Boosting is an ensamble learning method in which a set of weights is maintained over the training samples and adaptively adjusted after each training itteration according to the ones that are misclasified [1]. Given an individiual classifier h, an enamble of classifers can be constructed of a set of indvidual classifers, $H = h_1, h_2, ;h_n$. By maintaining a weight distribution over all of the training examples, these weights could be updated to emphasize the training examples that are misclassified incorrectly. These incorrectly classified examples could then be learned in a refinement of the classifier or by training adding a new classifer to the ensamble with the new



(a) Liver (b) Glass (c) Vowel

Fig. 1: Distribution of Class Data

weights. Performance of the ensamble is enhanced as long as the individual classifiers are weak and have uncorrelated errors as when any single classifer is incorrect the other classifiers in the ensamble might correctly classify the example.

II. Methods

A. Support Vector Machines

Suport vector machines were implemented with the libsvm library [2]. Radial basis functions were used as the kernal space for the SVM to create RBFSVM. There are then two parameters that need to be determined, C the regularization paramater and σ, the width of the kernal. These parameters where determined by a grid search of the parameter space. In searching for the optimal parameters with a grid search five fold cross valdation of the data was used. In addition, it was noticed for the vowel data sets that the large degree of accuracy was achieved by using a large amount of support vectors in which the SVM was essentially memorizing the training examples. This was mitigated by decreasing the error factor by passing the correct input argument to `svmtrain`.

B. AdaBoost

AdaBoost was implemented as an ensamble of support vector machines by maintaining a weight distribution of the misclassificaiton error over all of the training examples. At each cycle t AdaBoost provides the learning algorthim with training examples $\vec{x}$ and a weight distriubtion w (initialized uniformly). The learning algorthim is trained to generate a classifier h_t and the weight distribution is updated to reflect the predicted results; easy training examples (in which the classifier is very certain) have their weights lowered, while hard samples have their weights increased. This process continues for T cycles. Finally, the AdaBoost combines all of the component classifiers into the ensamble whose signal, final hypothesis, is constructed by by weighting the individual classifers by their training errors.

The AdaBoost algorthim (Algo 1 was extended to AdaBoostM1 in order to use the RBFSVM. This algorthim uses a fairly large RBFSVM kernal (a weak learning ability) for the first classifier, h_t. The classifier is then retrained with a smaller σ until the accuracy of the classifier has an accuracy of just over 50%. At this point the classifer is added to the ensamble, along with it's weight based on it's accuracy. The weights of the training samples are then updated to reflect the training examples that the classifier struggled with. This processes is then repeated for the next classifier in the ensamble until all of the ensamble is full.

Algorithm 1 AdaBoostSVM

procedure AdaBoostSVM($\sigma_{init}, \sigma_{min}, \sigma_{step}, C, \vec{x}, \vec{y}$)
  $w_i^1 \leftarrow 1/N\forall \quad i = 1, \dots, N$
  while $\sigma > \sigma_{min}$ **do**
Train a RBFSVM component classifier
    $h_t \leftarrow$ ComponentClassifer$(\vec{x}, \vec{w})$
Compute the error of that classifer
    $h_t \;:\; \epsilon_t = \sum_{i=1}^{N} w_i^t, y_i \neq h_t(\vec{x}_i)$
Decrease σ until a weak classifier
    if $\epsilon_t > 0.5$ **then**
      $\sigma = \sigma - \sigma_{step}$
      go to 3
    end if
Set weight of component classifer
    $h_t \;:\; \alpha_t = \frac{1}{2} ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$
Update weights of training samples
    $w_i^{t+1} = \frac{w_i^t exp(-\alpha_i y_i h_t(\vec{x}))}{C_t}$
C_t is a normalization value, $\sum_{i=1}^{N} w_i^{t+1} = 1$
  end while
return $f(\vec{x}) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(\vec{x})\right)$
end procedure

The choice of σ is critical for the algorthim presented to converge. Too small a σ and the RBFSVM tends to overfit the data and provide correlated classifiers (and thus their error will be correlated), while too large a value of σ and the classifer is too weak. The implemented algorthim only varied the value of σ because it is known that RBFSVMs depend highly on σ and less on C so the performance of the classifer can be changed over a set C by simply changing σ [1]. In addition ensamble sizes for 5 to 150 were tested, these results are shown in Section III.

Several experiments were completed once the code base was written. Three data sets were obtained from the LIBSVM homepage [2]. These data sets were parsed and scaled with the tools provided in the libsvm package. First the optimal number of ensamble methods was found by investignating the classification accuracy dependance on the number of support vectors. Next the AdaBoost implementation vs the accuracy acheived by the a single parameter grid search. Finally the classification errors between the two methods are analyzed.

III. Results

It can bee seen by Figure 1 that two of the data sets, the liver and glass, are imbalanced while the third, vowel, has each class equally represented. Furthermore it is observed that the glass data set is the most imbalanced; this is where the largest increase of performance due to the AdaBoostM1 is expected. The results of an SVM on the data sets is presented in Section III-A. In Section III-B the results are shown for using an ensamble methods.

A. Parmater Search

The parameter search for the optimal C and σ parameters is shown in the contour plots of Figures 2, 3 and 3. The liver and glass data set contour plots have many topological features indicating that small varations in the RBFSVMs parameters cause dramatic changes in the accuracy of the trained RBFSMV. The vowel data set does not display these features but rather has a plataue region atop a precipice in which the accuracy of the classifer does not change dramatically. The optimal classifier parameters are shown for the coarse parameter search in Table I and for the fine parameter search in Table II. C_{min} and C_{max} are the starting values of the grid search normalization parameter, σ_{min} and σ_{max} are the range of kernal size while C, σ and ϵ are the optimzied normalization parameter, kernal size, and final accuracy respectively. The values for the fine parameter search were chosen to be 50% of the optimal values selected by the coarse parameter search.

TABLE I: Coarse Optimal Classifier Parameters

Data Set	C_{min}	C_{max}	σ_{min}	σ_{max}	C	σ	ϵ
Glass	1.00	10.00	-7.00	7.00	1.00	3.89	66.67
Liver	1.00	10.00	-7.00	7.00	8.00	2.33	70.33
Vowel	1.00	10.00	-7.00	7.00	8.00	0.78	96.02

TABLE II: Fine Optimal Classifier Parameters

Data Set	C_{min}	C_{max}	σ_{min}	σ_{max}	C	σ	ϵ
Glass	0.50	1.50	1.94	5.83	1.50	3.69	68.89
Liver	4.00	12.00	1.17	3.50	10.69	1.36	74.00
Vowel	4.00	12.00	0.39	1.17	8.41	1.10	96.21

B. AdaBoostM1

The effect of the number of the classifers in the ensamble is shown in Figure 5. It was observed for the un-balanced data sets the number of classifiers is the ensamble did not have a large effect (past a minimum amount of 20). Furthermore, it was suprising to note that the accuracy of the ensambles was constant for the liver data set, while the vowel data set showed an almost periodic trend that died out as the number of classifiers increased. The glass data set exhibited signficant varatition; it is thought that this occurs because of the well in the paramater space (Figure 3).

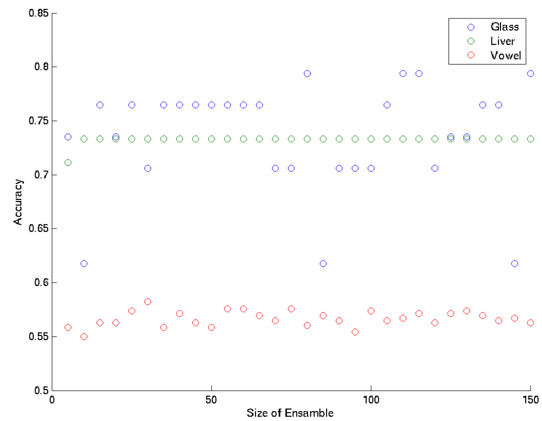


Fig. 5: Accuracy and Number of Compenents in Ensamble

The results using the implemented AdaBoostM1 algorthim are shown below in Table III, while the weights of the individual classifers (represnative of their accuracy) are shown in Figure 6. It is immediately observablve that the AdaBoost algorthim increased the accuarcy of the the Liver and Glass data set, but failed to increase (in fact dramatically lowered) the accuaracy for the Vowel data set. This is due to the vowel data set being balanced and each classifier being forced to be a weak classifier. When all of these weak classifiers are presented in an ensamble each classifer does not capature a specific region of the data set as the data set is balanced, but instead in the voting scheme cancel each other out, resulting in poor accuracy.

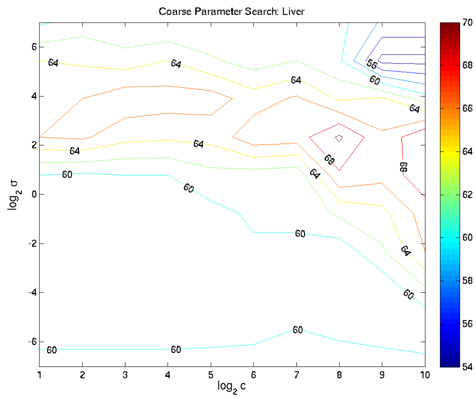
TABLE III: AdaBoost Classifer Values

Data Set	T	σ_{init}	C	ϵ
Glass	50	5.00	6.16	70.59
Liver	50	3.00	13.10	73.33
Vowel	50	2.00	10.00	56.49

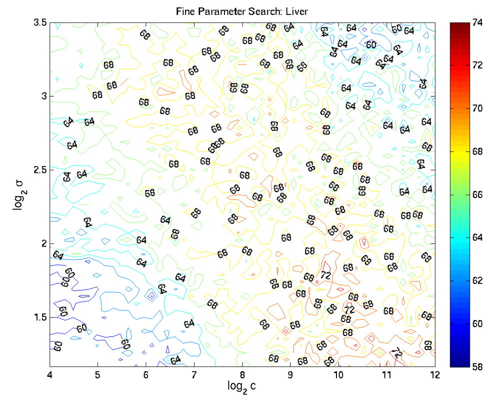
Data Set	T	σ_{init}	C	ϵ
Glass	100	5.00	6.16	73.53
Liver	100	3.00	13.10	73.33
Vowel	100	2.00	10.00	56.71

T is the total number of classifiers trained, σ_{init} is the initial σ presented to AdaBoostM1, C is the constant RBFSVM normalizaiton paramater, and ϵ is the accuracy of the ensamble method. Refer to Table II for the accuarcy of individual RBFSVM.

The weight of each individual classifer for an ensamble of 150 members is shown in Figure 6

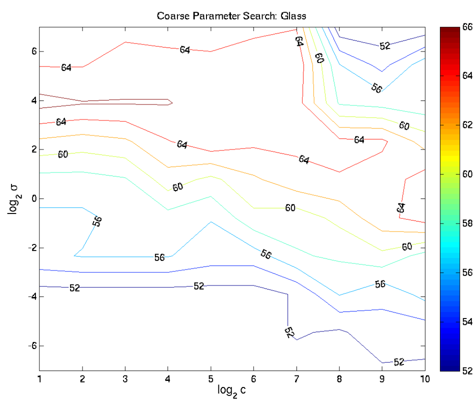


(a) Coarse Search

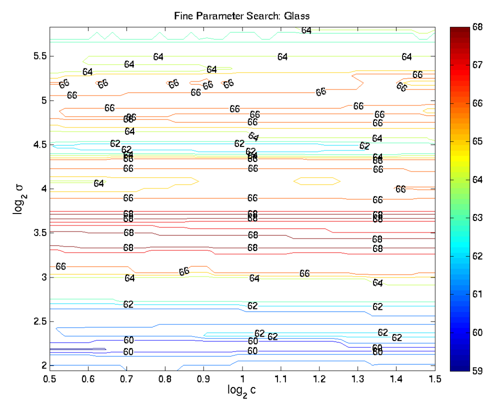


(b) Fine Search

Fig. 2: Parameter search for Liver Disorder

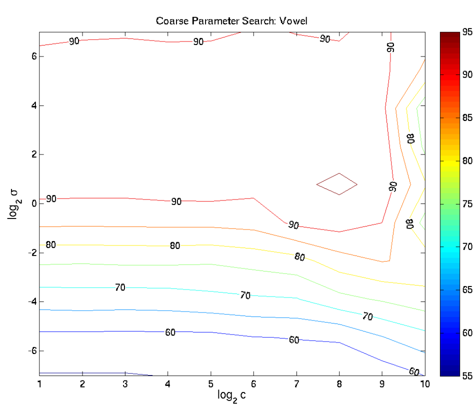


(c) Coarse Search

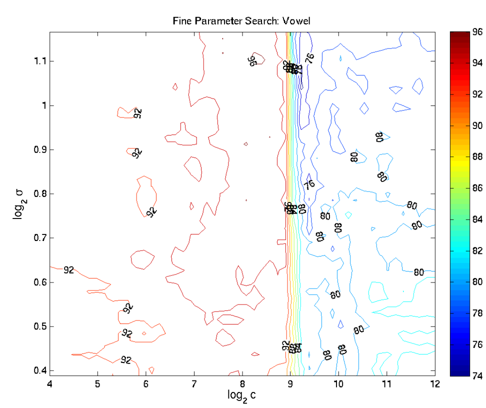


(d) Fine Search

Fig. 3: Parameter search for Glass Disorder

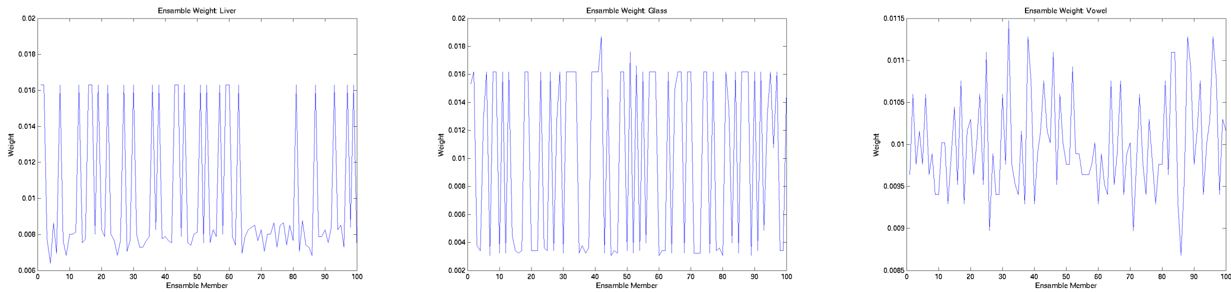


(a) Coarse Search



(b) Fine Search

Fig. 4: Parameter search for Vowel Disorder



(a) Liver (b) Glass (c) Vowel

Fig. 6: Distribution of Ensamble Weights

IV. Conclusions

Support vector machines were implemented on unbalanced data sets

The effect of having a large σ can be observed by examining Figures 2, 3 and 3. Larger values of σ tended to have a low accuracy, while too high a value tended to also have a low accuracy. Relatively large values of σ are then suited for the ensamble methods because they tend to be represenative of an RBFSVM which a relativly weak learning ability which generalizes better.

A. Future Work

Future work might be to change to use the decision value instead of the output class.

Acknowldegments

The conversations with Alan Nam of how to best use the LIBSVM library for the use of this project where extremely helpful. In addition Mike Franklin provided valuable comments on the structure of this project.

References

[1] X. Li, L. Wang, and E. Sung, "AdaBoost with SVM-based component classifiers," *Engineering Applications of Artificial Intelligence*, vol. 21, pp. 785–795, Aug. 2008.

[2] C. C. Chang and C. J. Lin, "LIBSVM: a library for support vector machines," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 2, no. 3, p. 27, 2011.