CAP5638 Project 2

Classification Using Linear Discriminant Functions and Boosting Algorithms

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December 2, 2015

The algorithms were implemented in Python 3.5, with a dependence on the *scipy* [1] library.

1 Basic Two-Class Classification Using Perceptron Algorithms

Abstractly, the problem is as follows: Given n labeled training samples, $D = \{(x_1, L_1), (x_2, L_2), ..., (x_n, L_n)\}$, where $L_i = \pm 1$, implement Algorithm 4 (Fixed-Increment Single-Sample Perceptron Algorithm) and Algorithm 8 (Batch Relaxation with Margin) of Chapter 5 in the textbook [2].

The algorithms are:

Algorithm 5.4 (Fixed-Increment Single-Sample Perceptron)

initialize $a, k = 0$
do $k \leftarrow (k+1) \mod n$
  if $\mathbf{y}_k$ is misclassified by $\mathbf{a}$ **then** $\mathbf{a} \leftarrow \mathbf{a} + \mathbf{y}_k$
until all patterns properly classified
return a

Algorithm 5.8 (Batch Relaxation with Margin)

initialize $a, \eta(\cdot), b, k \leftarrow 0$
do $k \leftarrow (k+1) \mod n$
  $\mathcal{Y}_k = \{\}$
  $j = 0$
  do $j \leftarrow j + 1$
    if $\mathbf{a}^t \mathbf{y}^j \leq b$ **then** Append $\mathbf{y}^j$ to $\mathcal{Y}_k$
  until $j = n$
  $\mathbf{a} \leftarrow \mathbf{a} + \eta(k) \sum_{y \in \mathcal{Y}} \frac{b - \mathbf{a}^t \mathbf{y}}{\|\mathbf{y}\|^2} \mathbf{y}$
until $\mathcal{Y}_k = \{\}$
return a

Results

Long training times proved problematic, due to the fact that it took greater than 100000 iterations to reach convergence using the fixed relaxation rule for the UCI wine data set. As such, the most significant result here is that the higher dimensional USPS handwritten digits data set converges much more rapidly than the UCI wine data set – by several orders of magnitude. Futhermore, for the fixed-increment rule, accuracy is much greater when testing on the handwritten digits data set. The batch relaxation rule performed well for both data sets, though higher on average for the UCI wine data set.

This most likely has to do with the fact that the handwritten digits data set has a great deal more training samples than the wine data set. With more training samples to update the hyperplane, the classifier can converge to a solution much more rapidly.

As for the long training times for the wine data set, the updated weights $\mathbf{a}(k)$ would oscillate between values for a long time before settling on a steady solution. To prevent this behaviour, several early termination heuristics were used. The heuristics were:

1. Always terminate after 100,000 iterations, and using the value of $\mathbf{a}$ that minimizes $J_p(\mathbf{a})$ for Algorithm 5.4 and $J_r(\mathbf{a})$ for Algorithm 5.8.

2. Terminate if, after 50,000 iterations, $||\mathbf{a}(k+1) - \mathbf{a}(k)|| \approx 0$, and $J_p(\mathbf{a}) \approx 0$ for Algorithm 5.4 and $J_r(\mathbf{a}) \approx 0$ for Algorithm 5.8.

Most likely, the necessity for early termination is due to the fact that the mean and standard deviation of the training samples was not normalized (however, the perceptron was trained using normalized augmented features, e.g. for training label ω_1, $y_i^T = [1, \mathbf{x_i}]$ if x_i belongs to ω_1, and $y_i^T = [-1, -\mathbf{x_i}]$ if x_i is not a sample for ω_1.

It's very likely that these early-termination heuristics had a detrimental effect on the classification accuracy, since in these cases, the there was no guarantee that $\mathbf{a}^T\mathbf{y} \geq 0$ for all augmented $\mathbf{y}$.

UCI Wine Data Set

Algorithm 5.4 (Fixed-Increment Single-Sample Perceptron)

Training Statistics			
Class	**Correct (of 89) (%)**	**Iterations**	**Runtime(s)**
ω_1	60 (67.42%)	100001	63.151
ω_2	56 (62.92%)	100001	63.050
ω_3	85 (95.51%)	84710	53.850
Total		284710	180.051

The corresponding weights after training were:

$$\mathbf{a}_{\omega_1} = \begin{bmatrix} -2. \\ -23.54 \\ -1.28 \\ -3.54 \\ -36.8 \\ -136. \\ -2.7 \\ 0.36 \\ -1.34 \\ 2.3 \\ -2.86 \\ -2.88 \\ -0.42 \\ -490. \end{bmatrix} \quad \mathbf{a}_{\omega_2} = \begin{bmatrix} 9484.0 \\ 56298.47 \\ -26970.62 \\ 9950.26 \\ -10456.6 \\ -3765. \\ 55712.08 \\ -1502.68 \\ 36611.34 \\ -40821.68 \\ -109006.33 \\ 65677.49 \\ 44053.19 \\ -430.0 \end{bmatrix} \quad \mathbf{a}_{\omega_3} = \begin{bmatrix} 451.0 \\ -1399.63 \\ -10081.3 \\ -16667.88 \\ 28250.3 \\ 2665.0 \\ -71066.41 \\ -107364.33 \\ -12267.75 \\ -24570.91 \\ 94303.98 \\ -52048.4 \\ -132265.0 \\ -958.0 \end{bmatrix}$$

Algorithm 5.8 (Batch Relaxation with Margin)

Training Statistics			
Class	**Correct (of 89) (%)**	**Iterations**	**Runtime(s)**
ω_1	87 (97.75%)	22864	27.498
ω_2	85 (95.51%)	52918	62.130
ω_3	83 (93.26%)	35600	127.227
Total		111,382	216.855

The corresponding weights after training were:

$$\mathbf{a}_{\omega_1} = \begin{bmatrix} 0.796 \\ -0.31 \\ 0.768 \\ 0.183 \\ -0.362 \\ -0.063 \\ 0.74 \\ 0.153 \\ 0.867 \\ 0.601 \\ 0.128 \\ 0.216 \\ 0.583 \\ 0.01 \end{bmatrix} \quad \mathbf{a}_{\omega_2} = \begin{bmatrix} 261.354 \\ 869.172 \\ -1800.878 \\ -101.749 \\ 1335.277 \\ 6.557 \\ 1335.119 \\ 1928.754 \\ 99.223 \\ 921.129 \\ -6428.793 \\ 895.385 \\ 2459.442 \\ -33.943 \end{bmatrix} \quad \mathbf{a}_{\omega_1} = \begin{bmatrix} 0.855 \\ -0.161 \\ 0.587 \\ 0.188 \\ -0.108 \\ -0.017 \\ 0.295 \\ -0.334 \\ 0.758 \\ -0.18 \\ 0.882 \\ -0.084 \\ 0.086 \\ -0.003 \end{bmatrix}$$

USPS Handwritten Digits Data Set

Algorithm 5.4 (Fixed-Increment Single-Sample Perceptron)

Training Statistics			
Class	**Correct (of 2007) (%)**	**Iterations**	**Runtime(s)**
ω_0	1928 (96.06%)	17 trials	0.031
ω_1	1982 (98.75%)	9 trials	0.018
ω_2	1873 (93.32%)	14 trials	0.026
ω_3	1896 (94.47%)	14 trials	0.033
ω_4	1897 (94.52%)	23 trials	0.040
ω_5	1905 (94.92%)	22 trials	0.042
ω_6	1960 (97.66%)	25 trials	0.047
ω_7	1926 (95.96%	25 trials	0.045
ω_8	1881 (93.72%)	20 trials	0.037
ω_9	1919 (95.62%)	41 trials	0.073
Total		210	0.392

The weights are too large to display in the report, however they can be displayed by invoking the following command using the included run.py script:

python3 run.py fixed bin/digits_train.txt bin/digits_test.txt

Algorithm 5.8 (Batch Relaxation with Margin)

Training Statistics			
Class	**Correct (of 2007) (%)**	**Iterations**	**Runtime(s)**
ω_0	1837 (91.53%)	717	1.297
ω_1	1917 (95.52%)	742	1.277
ω_2	1850 (92.18%)	606	1.084
ω_3	1894 (94.37%)	434	0.744
ω_4	1843 (91.83%)	597	1.130
ω_5	1900 (94.67%)	825	1.571
ω_6	1891 (94.22%)	831	1.612
ω_7	1904 (94.87%)	1358	2.581
ω_8	1863 (92.83%)	934	1.907
ω_9	1898 (94.57%)	1649	3.331
Total		18797	16.535

The weights are too large to display in the report, however they can be displayed by invoking the following command using the included run.py script:

python3 run.py relax bin/digits_train.txt bin/digits_test.txt

2 Multi-Class Classification

For this classification method, both the fixed-increment and batch relaxation training rules from the previous section were used for testing.

For one-against-the-rest classification, a sample was classified as ω_i if $\mathbf{a}_i^T\mathbf{x} \geq \mathbf{a}_j^T\mathbf{x}$ for all $i \neq j$.

For one-against-other classification... TODO

Results

(Note: The runtime statistics for training are tabulated in the previous section)

UCI Wine Data Set

One-Against-the-Rest

Using the fixed increment rule (Algorithm 5.4 above), the one-against-the-rest classifier correctly classified 68 testing samples out of 89 (76.40% accuracy). There were 111382 iterations during training (taking ≈ 216.855 seconds).

Using the batch relaxation rule (Algorithm 5.8), the one-against-the-rest classifier correctly classified 85 testing samples out of 89 (95.51% accuracy). There were 300000 iterations during training (taking ≈ 398.827 seconds).

One-Against-the-Other

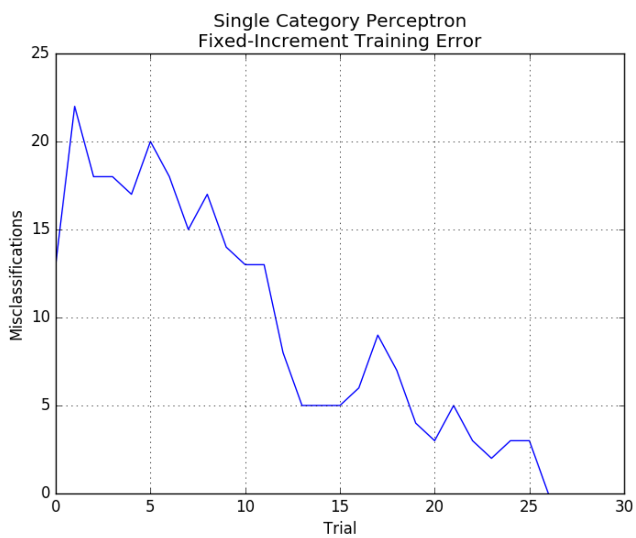
TODO

USPS Handwritten Digits Data Set

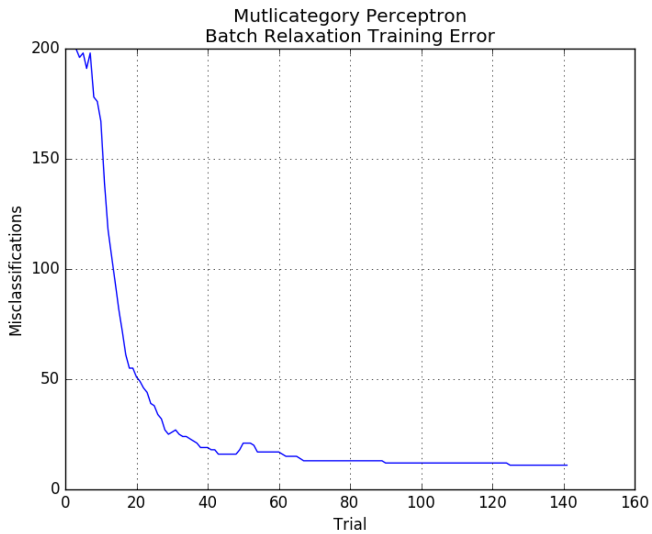
One-Against-the-Rest

Completed training after 27 trials. Total training time: 2.923
1617 correct out of 2007 (80.57 accuracy)

Using the fixed increment rule (Algorithm 5.4 above), the one-against-the-rest classifier correctly classified 1608 samples out of 2007 (80.12% accuracy). Training occured over 177 iterations (≈ 0.571 seconds).



Using the batch relaxation rule (Algorithm 5.8), the one-against-the-rest classifier correctly classified 1626 testing samples out of 2007 (81.02% accuracy). Training occured over 142 training trials (≈ 23.032 seconds).



One-Against-the-Other

3 Adaboost to Create Strong Classifers

Implement Algorithm 1 (AdaBoost) in Chapter 9 of the textbook to create a strong classifier using the above linear discriminant functions.

Algorithm 9.1 (AdaBoost)

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initialize $\mathcal{D} = \left\{\mathbf{x}^1, y_1, ..., \mathbf{x}^n, y_n\right\}, k_{max}, W_1(i) = 1/n, i = 1...n$

$k = 0$

do $k \leftarrow k + 1$

  train weak learner C_k using $\mathcal{D}$ sampled according to $W_k(i)$

  $E_k \leftarrow$ training error of C_k measured on $\mathcal{D}$ using $W_k(i)$

  $\alpha_k \leftarrow 0.5 \ln\left[(1 - E_k)/E_k\right]$

  $W_{k+1}(i) = \frac{W_k(i)}{Z_k} \times \begin{cases} e^{-\alpha_k} & \text{if } h_x(\mathbf{x}^i) = y_i \text{ (correct classification)} \\ e^{\alpha_k} & \text{if } h_k(\mathbf{x}^i) \neq y_i \text{ (incorrect classification)} \end{cases}$

until $k = k_{max}$

return C_k and α_k for $k = 1$ to k_{max} (ensemble of classifiers with weights)

Results

Boost Algorithm 8 to create a strong classifier for class 1 vs. class 2, class 1 vs. class 3, and class 2 vs. class 3 on the two datasets. Then classify the corresponding test samples from the relevant classes in test sets (in other words, for example, for the class 1 vs. class 2 classifier, you only need to classify test samples from classes 1 and 2); then document classification accuracy and show and analyze the improvement.

UCI Wine Data Set

USPS Handwritten Digits Data Set

4 Extra Credit

4.1 Support vector machines

By using an available quadratic programming optimizer or an SVM library, implement a training and classification algorithm for support vector machines. Then use your algorithm on the USPS dataset. Document the classification accuracy and compare the results with that from the two basic algorithms.

Results

TODO

4.2 Kernel method for linear discriminant functions

Given a kernel function, derive the kernel-version of Algorithm 4 and implement the algorithm, and then apply it on the given wine and USPS datasets. Document the classification accuracy and compare the results with that from the two basic algorithms without kernels. Use the polynomial function of degree three as the kernel function; optionally, you can use other commonly used kernel functions.

Results

TODO

4.3 Multiple-class linear machines and multiple-class boosting

Use the Keslers construction to train a linear machine for multi-class classification and then use the SAMME algorithm to boost its performance on the training set. Apply the algorithm on both datasets and classify the corresponding test samples in the test sets. Document the classification accuracy and compare the results with that from the one-against-the-rest and one-against-the- other algorithms.

4.3.1 Results

TODO

References

[1] Jones E, Oliphant E, Peterson P, *et al.* **SciPy: Open Source Scientific Tools for Python**, 2001-, `http://www.scipy.org/` [Online; accessed 2015-10-24].

[2] Richard O. Duda, Peter E. Hart, and David G. Stork **Pattern Classification** 2nd edition