CS6140 Machine Learning

HW5 - Features

Make sure you check the syllabus for the due date. Please use the notations adopted in class, even if the problem is stated in the book using a different notation.

SpamBase-Poluted dataset: the same datapoints as in the original Spambase dataset, only with a lot more columns (features) : either random values, or somewhat loose features, or duplicated original features.

SpamBase-Poluted with missing values dataset: train, test. Same dataset, except some values (picked at random) have been deleted.

Digits Dataset (Training data, labels. Testing data, labels): about 60,000 images, each 28x28 pixels representing digit scans. Each image is labeled with the digit represented, one of 10 classes: 0,1,2,...,9.

PROBLEM 1 Adaboost with bad features[50 points]

A) Spambase (original dataset) : Implement feature analysis for Adaboost as part of your boosting code. Run Adaboost with Decision Stumps for 300 rounds; then list the top ten features : rank features by the fraction of average margin (of the overall classifier) due to each feature.
Cheng's top 15 features (IDs as column number in data, starting at 0): 52, 51, 56, 15, 6, 22, 23, 4, 26, 24, 7, 54, 5, 19, 18.

B) Spambase polluted dataset : Run Adaboost on polluted Spambase and report performance - why does it still work? Expected Accuracy: 93%.

PROBLEM 2 PCA [50 points]

Spambase polluted dataset.
A) Train and test Naive Bayes. Why the dramatic decrease in performance ? Expected Accuracy with Gaussian Fits: 62%

B) Run PCA first on the dataset in order to reduce dimensionality to about 100 features. You can use a PCA package or library of your choice.
Then train/test Naive Bayes on the PCA features. Explain the performance improvement. (To make it work, you have to apply PCA consistently to training and testing points: either apply for training and store the PCA transformation to apply it later for each test point; or apply PCA once for entire dataset)
Expected Accuracy on Naive Bayes with Gaussian Fits, running on PCA features: 73%.

C) **[Extra Credit]** Implement your own PCA, and rerun Naive Bayes on obtained features.

D) **[Extra Credit]** Run LDA instead of PCA before you train the Naive Bayes. You can use a LDA package or library of your choice.

PROBLEM 3 Regularized Regression for feature selection [50 points]

A) Spambase polluted dataset run Logistic Regression for classification. Expected Accuracy: 85%

B) Run Regularized Regression using either a LASSO and RIDGE package for regularization. (For example use the scikit-learn (Python) or Liblinear (C++) implementation of LASSO.) Compare with Logistic Regression performance. Expected Accuracy of Lasso Logistic Regression: 93%.

C) Implement your own RIDGE optimization for Logistic Regression. Expected Accuracy of Ridge Logistic Regression: 92%.

D) **[Extra Credit]** Implement your own LASSO optimization for linear regression.

PROBLEM 4 Missing Values [30 points]

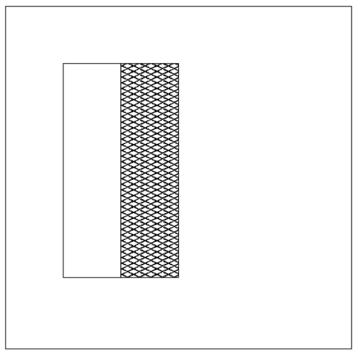
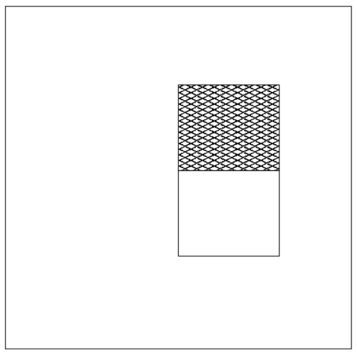
Spambase poluted dataset with missing values: train, test. Run a slightly modified Naive Bayes to deal with the missing values, as described in notes following KMurphy 8.6.2. (Essentially runs the independence product from Naive Bayes ignoring the factors corresponding to missing features.)
Expected Accuracy when using Bernoulli fits: 80%.

PROBLEM 5 Image Feature Extraction [50 points]

Implement and run HAAR feature Extraction for each image on the Digit Dataset. Then train and test a 10-class ECOC-Boosting on the extracted features and report performance. You can sample the training set (say 20% of each class), in order to scale down the computation.
Expected Accuracy when using 200 HAAR features, 50 random ECOC, each Adaboost trained for 200 rounds: 89%.

(**Hint:** For extracting the MNIST dataset, here are the codes for Python , MATLAB and Java)

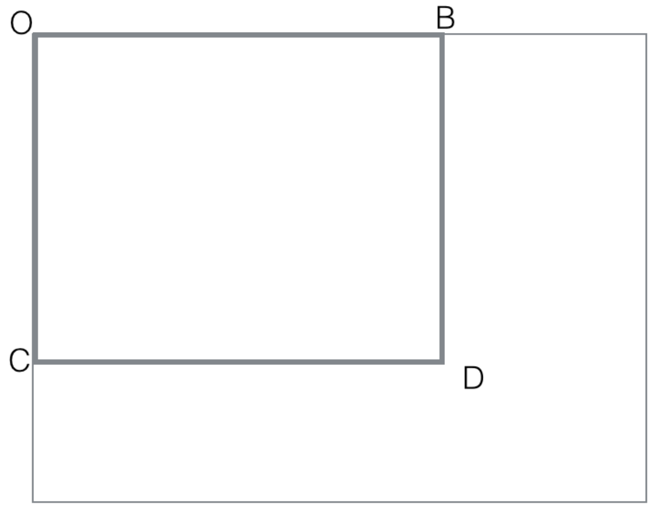
HAAR features for Digits Dataset :First randomly select/generate 100 rectangles fitting inside 28x28 image box. A good idea (not mandatory) is to make rectangle be constrained to have approx 130-170 area, which implies each side should be at least 5. The set of rectangles is fixed for all images. For each image, extract two HAAR features per rectangle (total 200 features):

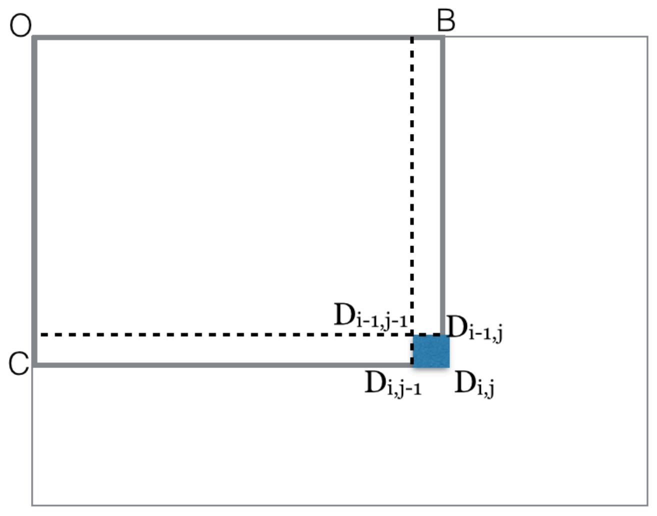



- the black horizontal difference black(left-half) - black(right-half)
- the black vertical difference black(top-half) - black(bottom-half)

You will need to implement efficiently a method to compute the black amount (number of pixels) in a rectangle, essentially a procedure black(rectangle). Make sure you follow the idea presented in notes : first compute all black (rectangle OBCD) with O fixed corner of an image. These O-cornered rectangles can be computed efficiently with dynamic programming

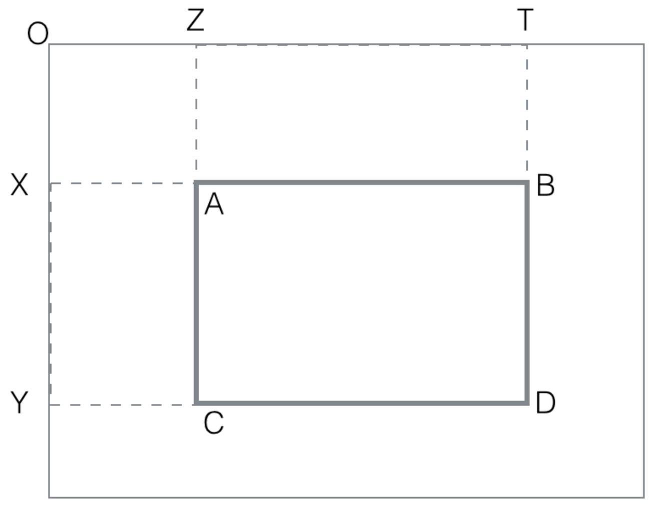
```
black(rectangle OBCD)= black(rectangle-diag(OD)) = count of black points
in OBCD matrix
for i=rows
for j=columns
    black(rectangle-diag($OD_{ij}$)) = black(rectangle-diag($OD_{i,j-1}$)) +
black(rectangle-diag($OD_{i-1,j}$))
                                - black(rectangle-diag($OD_{i-1,j-1}$)) +
black(pixel $D_{ij}$)
end for
end for
```





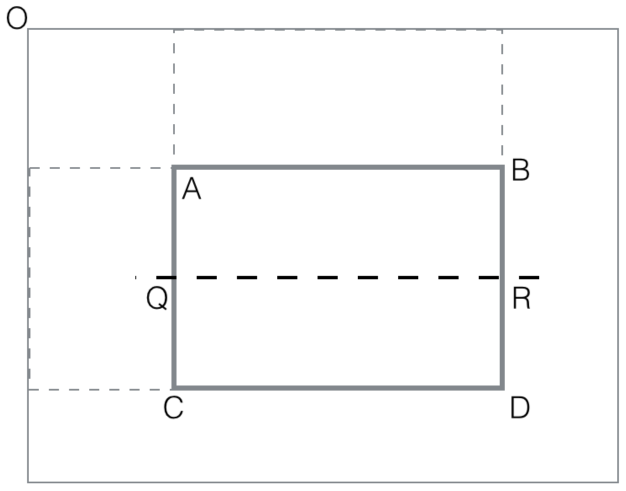
Assuming all such rectangles cornered at O have their black computed and stored, the procedure for general rectangles is quite easy:

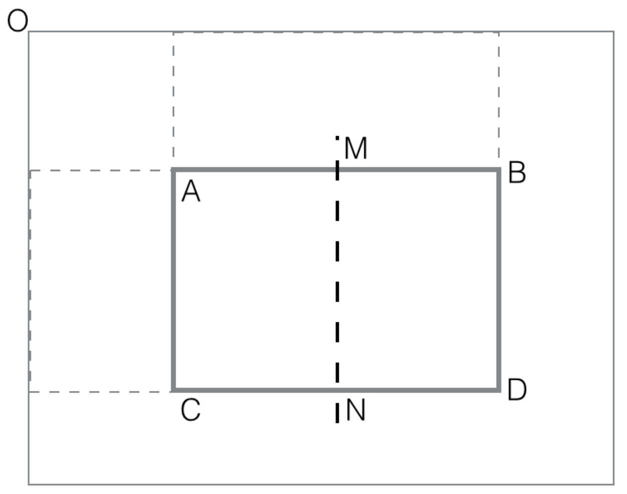
```
black(rectangle ABCD) = black(OTYD) - black(OTXB) - black(OZYC) +
black(OZXA)
```



The last step is to compute the two feature (horizontal, vertical) values as differences:

```
vertical_feature_value(rectangle ABCD) = black(ABQR) - black(QRCD)
horizontal_feature_value(rectangle ABCD) = black(AMCN) - black(MBND)
```





PROBLEM 6 Boosting with Dynamic Features [Extra Credit]

A) Run Boosting (Adaboost or Rankboost or Gradient Boosting) to text documents from 20 Newsgroups without extracting features in advance. Extract features for each round of boosting based on current boosting weights.

B) Run Boosting (Adaboost or Rankboost or Gradient Boosting) to image datapoints from Digit Dataset without extracting features in advance. Extract features for each round of boosting based on current boosting weights. You can follow this paper.