CS 335: Lab Assignment 3

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Acknowledgment: This lab assignment is partly based on Project 5: Classification, which is a part of a recent offering of CS188 at UC Berkeley. We thank the authors at Berkeley for making their project available to the public.

Ensemble Learning, a form of meta-learning, is a machine learning paradigm where multiple learners are trained to solve the same problem. In this assignment, you will code up the meta-learning algorithms **Bagging** (short for **Bootstrap Aggregating**) and **Boosting** (specifically **AdaBoost**). These meta-learners will operate on the **Perceptron** as a base learner, which you have already worked on in Lab Assignment 1.

(Image source: https://scroll.in/magazine/872431/sofar-sounds-a-unique-initiative-allows-musicians-and-audiences-to-discover-one-another-in-india)

The data set on which you will run your meta-learning algorithms is a collection of handwritten numerical digits ($0 - 9$). However we have decided to have you solve only a two-class problem. Hence, classes $0 - 4$ have the label -1, and classes $5 - 9$ have the label 1. Details about your tasks, and the files you must submit as a part of this assignment, are mentioned in the sections below.

Code

The base code for this assignment is available in this zip file. You need to use these files from the `ensembling` directory.

File Name	**Description**
answers.txt	Blank text file for you to enter answers from Task 2 and Task 3.
autograder.py	This is used for testing your Task 2 and Task 3
bagging.py	The file where you will write your bagging classifier.
boosting.py	The file where you will write your boosting classifier.
classificationMethod.py	Abstract super class for the classifiers you will write. You **should** read this file carefully to see how the infrastructure is set up. Do **not** edit this file.
createBaggingData.sh	Bash script that runs the classifiers on several different counts of weak classifiers.
createBoostingData.sh	Bash script that runs the classifiers on several different counts of weak classifiers.
createGraphBagging.gnuplot	Gnuplot script to plot accuracy versus number of weak classifiers.
createGraphBoosting.gnuplot	Gnuplot script to plot accuracy versus number of weak classifiers.
data.zip	Contains the training, validation and test data sets.
dataClassifier.py	The wrapper code that will call your classifiers.
perceptron.py	The file where you will write your perceptron classifier.
samples.py	I/O code to read in the classification data. Do **not** edit this file.
util.py	Code defining some useful tools, that will save you a lot of time. Do **not** edit this file.

Task 0: Implementing the 2-class Perceptron Again (Ungraded)

In this task, you have to implement the 2-class Perceptron classifier. Fill out code in the `train()` function at the location indicated in `perceptron.py`. Using the addition, subtraction, and multiplication functionality of the `Counter` class in `util.py`, the perceptron updates should be relatively easy to code. You can and are advised to use code from Lab Assignment 1, while keeping in mind you are solving a 2-class problem.

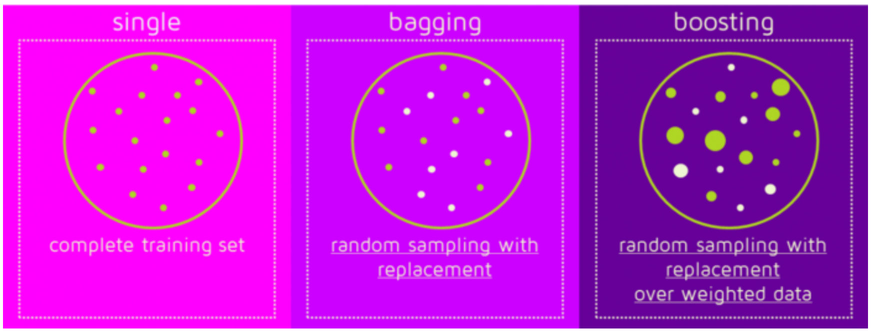
Run your code with the following command.

```
python dataClassifier.py -c perceptron -t 1000 -s 1000
```

The classifier should be able to get an accuracy of 65% - 70%.

Task 1: Understanding the Ensemble Algorithms (Ungraded)

Bagging and boosting are in the spirit of learning a strong classifier from a set of weak classifiers. The main difference lies in the way they choose data sets for training each base learner.


single
complete training set
bagging
random sampling with replacement
boosting
random sampling with replacement over weighted data

(Image source: https://quantdare.com/wp-content/uploads/2016/04/bb2-1150x441.png)

1) The Bootstrap Aggregating Algorithm

Given a standard training set D of size N, bagging generates M new training sets $\{D_m\}_{m=1}^{M}$, each of size N', by sampling from D uniformly at random and with replacement. By sampling with replacement, some observations may be repeated in each D_m. These data sets are significantly different from each other as only about 63% of the original data set will appear in any of D_m if $N = N'$.

The data sets generated $D_1, D_2, \ldots, D_M$ are fed to individual weak learners $h_1, h_2, \ldots, h_M$, respectively. This brings out the most important characteristic of bagging which gives it a definitive advantage over boosting in terms of speed, that you can train weak learners in parallel.

Finally, for a new data point x, it is fed into each of the weak learners $\{h_m\}_{m=1}^{M}$. The outputs from each weak learner $y'_1, y'_2, \ldots, y'_M$ is then polled to find the label whose count is maximum. In other words,

$y = sign(\sum_{m=1}^{M} y'_m)$.

2) The AdaBoost Algorithm

The AdaBoost algorithm in each iteration trains a new weak learner with the same data set D but with associated weights for each sample: $w_1, w_2, \ldots, w_N$. After training, each misclassified point is weighed up so that in the next training iteration the weak learner classifies them correctly. Also a set of hypothesis weights $z_1, z_2, \ldots, z_M$ are computed for each $h_1, h_2, \ldots, h_M$ respectively which determine the effectiveness of the corresponding hypotheses.

The output for a new data point x is obtained by thresholding a weighted summation of the labels $y'_1, y'_2, \ldots, y'_M$ produced by each weak learner weighed according to the hypothesis weights:

$y = sign(\sum_{m=1}^{M} y'_m \times z_m)$

Refer to Section 18.10 of Russell and Norvig (2010) for a detailed description.

Task 2: Implementation of Bagging (3 marks)

Your task is to implement the 2-class bagging classifier with perceptron as the weak learner. Fill out code in the `train()` and `classify()` functions at the location indicated in `bagging.py`.

`train()` should contain the code to sample points from the data set with replacement and then training the weak classifier using the sampled data set. `classify()` should contain the code to get the labels from individual classifiers and then running voting to find the majority.

Note: We do **not** expect you to write parallel code for this task.

Run your code with the following command.

```
python dataClassifier.py -c bagging -t 1000 -s 1000 -r 1 -n 20
```

Evaluation: Your classifier will be evaluated for its accuracy on the test set after the Bagging algorithm has been run with weak learners trained for the default 3 iterations. You will be awarded 3 marks if the accuracy exceeds 75%, otherwise 2 marks if the accuracy exceeds 73%, otherwise 1 mark if the accuracy exceeds 71%, otherwise 0 marks.

The autograder Script for this task is as follows.

```
python autograder.py -t 2
```

Task 3: Implementation of AdaBoost (4 marks)

In this task you have to implement the 2-class adaboost classifier with perceptron as the weak learner. Fill out code in the `train()` and `classify()` function at the location indicated in `boosting.py`. Also you will have to fill the `sample_data()` function in `perceptron.py` which converts a weighted data set to an unweighted one. Remember that perceptron algorithm doesn't work with weights assigned to individual samples. The size of the sampled data set should be set to within **0.5 - 1.5 times** the size of original data set.

`train()` should contain the code to compute the weights for each data point after training the weak classifier. `classify()` should contain the code to get the labels from individual classifiers and then have weighted summation to get the final output.

Run your code with the following command.

```
python dataClassifier.py -c boosting -t 1000 -s 1000 -b 20
```

Evaluation: Your classifier will be evaluated for its accuracy on the test set after the AdaBoost algorithm has been run with weak learners trained for the default 3 iterations. You will be awarded 4 marks if the accuracy exceeds 75%, otherwise 3 marks if the accuracy exceeds 74%, otherwise 2 marks if accuracy exceeds 73%, otherwise 1 mark if the accuracy exceeds 71%, otherwise 0 marks.

The autograder script for this task is as follows.

```
python autograder.py -t 3
```

Task 4: Analysing the Ensemble Algorithms' performance (3 marks)

Variation with number of weak classifiers: Here, you will see the influence of number of weak classifier on the accuracy of validation set, when trained for the same number of iterations.

Every time `dataClassifier.py` is run, it writes a comma-separated pair of numbers—<number of classifiers>,<accuracy>—for the train, the validation and the test sets to files `{classifier}_train.csv`, `{classifier}_val.csv` and `{classifier}_test.csv`. Use `create{classifier}Data.sh` (supplied in the zip file) to run the algorithm with 1, 3, 5, 7, 9, 10, 13, 15, 17, 20 weak classifiers. Create a plot named `plot_{classifier}.png` by running `createGraph{classifier}.gnuplot`. Below are commands to generate the required graph.

- `./create{classifier}Data.sh`
- `gnuplot createGraph{classifier}.gnuplot`

Note: It takes quite a lot of time to generate the numbers, so keep **1 day** just for running the scripts before the final submission deadline.

Feel free to experiment with the various switches and write a description of your observations and a description of the nature of the plot in the file `answers.txt` in plain text for both the algorithms. Additionally, answer the following question.

1. Compare the training accuracies of both the algorithms and explain your observations from a theoretical point of view.
2. "An ensemble combining perceptrons with weighted majority **cannot** be represented as an equivalent single perceptron." IS the above statement true? Give proper justification to your claim and accompany with examples if possible.

Submission

You are expected to work on this assignment by yourself. You may not consult with your classmates or anybody else about their solutions. You are also not to look at solutions to this assignment or related ones on the Internet. You are allowed to use resources on the Internet for programming (say to understand a particular command or a data structure), and also to understand concepts (so a Wikipedia page or someone's lecture notes or a textbook can certainly be consulted). However, you **must** list every resource you have consulted or used in a file named `references.txt`, explaining exactly how the resource was used. Failure to list all your sources will be considered an academic violation.

Be sure to write all the observations/explanations in the **`answers.txt`** file. We have mentioned wherever there is such a requirement. Find the keyword **`'answers.txt'`** in the page.

Place all files in which you have written code in or modified in a directory named `la3-rollno`, where `rollno` is your roll number (say 12345678). Tar and Gzip the directory to produce a single compressed file (say `la3-12345678.tar.gz`). It must contain the following files.

1. `perceptron.py`
2. `bagging.py`
3. `boosting.py`
4. `answers.txt`
5. `plot_bagging.png`
6. `plot_boosting.png`
7. `references.txt`

Submit this compressed file on Moodle, under Lab Assignment 3.