CS 335: Lab Assignment 1

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Acknowledgment: This lab assignment is inspired by 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. We also acknowledge the authors of the Kaggle shapes data set, which we use as a part of this assignment.

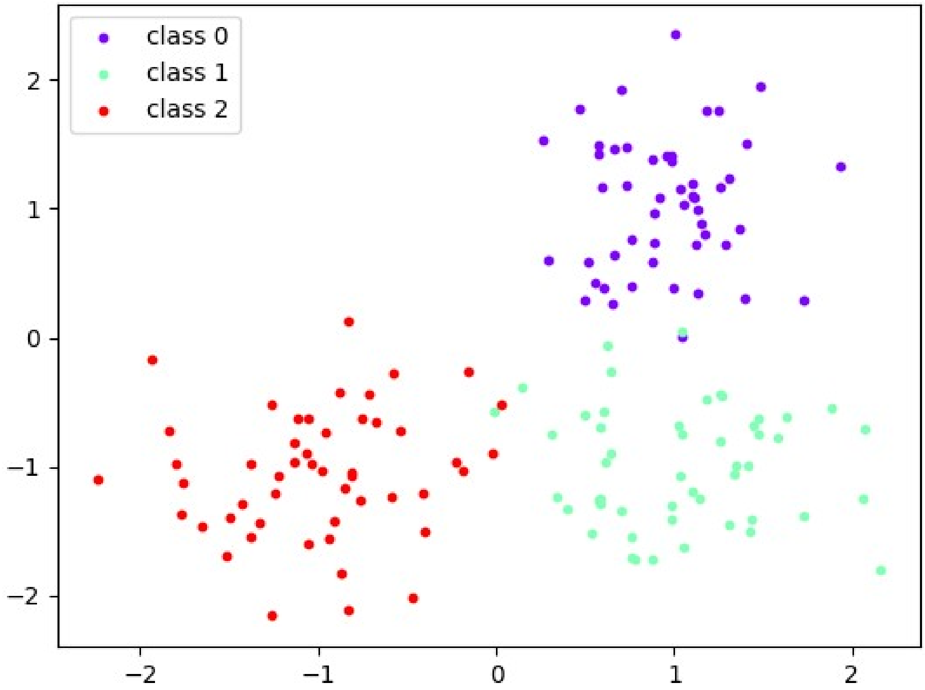
In this assignment, you will design a **multi-class** classifier on a set of d-dimensional points: specifically a **Perceptron** classifier. You will be implementing 2 different types of the multi class perceptron. The initial tasks would be to implement the two different methods to model multi-class perceptron (namely, 1-vs-rest and 1-vs-1) and analyze the results on the given dataset of d dimensional points. Subsequently, you will have to use the same classifier on a new data set of shape images, for which you will also have to design suitable features.

Data Sets

Data directory.

Data Set 1 (D1): d-dimensional points data

The data set on which you will run your classifiers is a collection of d-dimensional points which belong to k different classes. The method of generating the data points is as follows: pick k different corners of a d-dimensional hypercube $\{1, -1\}^d$. We sample data from a multivariate gaussian centered at these points. The standard deviation matrix of the multivariate gaussian used is the matrix diag([sigma]*d): that is, the diagonal matrix with all diagonal entries as sigma. These sampled points are your input data.
For example, consider the case when d = 2 and k = 3. The hypercube is the square ${[1,1], [1,-1], [-1,1], [-1,-1]}$. Choosing 3 centres from this set, the centres of gaussians are ${[1, 1], [1, -1], [-1,-1]}$. The sampled points are plotted for each of the classes using sigma = 0.5.



Visual Representaion of the 2D Example with 3 classes

In our case, the dimensions of data **d = 20**, the number of classes **k = 10** and the **sigma** in consideration is **1.5**. 100000 such data points along with the corresponding labels (classes) are generated. Out of these 80000 points are kept for training and 20000 points for testing. These are provided in `data/D1` directory. For Task 3.1 we will be using limited data from this data set (8000 train and 2000 test), referring to it as D1.2.

Data Set 2 (D2): Shape Images Data

This data set contains black and white 50x50 pixel sized images of different shapes. There are 1000 samples of 4 different shapes. We have attached the images as well as the extracted points from the shapes in the `data/D2 directory`. The extracted shapes will be in the form of a list with value '1' being black and '0' white. The list is generated using a row major scan of the image. The four classes labels are as follows : $['0' : circle, '1' : square, '2' : triangle, '3' : star]$. You can see the variation in the shapes, these variations are due to camera pose differences.

Code

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

File Name	Description
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.
createData.sh	Bash script that runs the perceptron (1 vs rest) classifier on several different sizes of the training set.
createGraphIterations.gnuplot	Gnuplot script to plot accuracy versus number of training examples seen.

createGraphTraining.gnuplot	Gnuplot script to plot accuracy versus size of the training set.
data	Contains the training and test data for both data sets.
dataClassifier.py	The wrapper code that will call your classifiers. You will also write your enhanced feature extractor here.
answers.txt	Blank text file for you to enter answers from Task 2 and Task 3.
perceptron1vr.py	The file where you will write your first perceptron (1 vs rest) classifier.
perceptron1v1.py	The file where you will write your second perceptron (1 vs 1) classifier.
autograder.py	The file we will be using to test your assignment. Do **not** edit this file.
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.
references.txt	In which you will note down every site/resource to which you have referred while working on this assignment.

Task 0: Understanding the Multi-class Perceptron (Ungraded)

There exist two broad techniques to solve the multi-class classification problem (see this link for an overview). We will be implementing and comparing both these techniques in this assignment.

1) The One-vs-rest (1vr) Multi-class Perceptron

A Perceptron keeps a weight vector $w^y$ corresponding to each class $y$ ($y$ is a suffix, not an exponent). Given a feature list $f$ (a vector with the same number of dimensions as the weight vectors), the perceptron computes the class $y$ whose weight vector is most similar to the input vector $f$. Formally, given a feature vector $f$ (in D1 (the point itself) and in D2 (a list of indicators for pixels being on)), we score each class $y$ with $$score(f, y) = \Sigma_i f_i w_i^y$$ where $i$ iterates over the dimensions in the data. Then we choose the class with the highest score as the predicted label for data instance $f$. In the code, we will represent $w^y$ as a Counter (defined in the file `util.py`).

Learning the weights of the Perceptron

In the basic multi-class Perceptron, we scan over the training data one instance at a time. When we come to an instance $(f,y)$, we find the label with highest score: $y\prime=argmax_{y\prime\prime}score(f,y\prime \prime)$, breaking ties arbitrarily. We compare $y\prime$ to the true label $y$. If $y\prime=y$, we have correctly classified the instance, and we do nothing. Otherwise, we predicted $y\prime$ when we should have predicted $y$. That means that $w_y$ has scored $f$ lower, and/or $w_{y\prime}$ has scored $f$ higher, than what would have been ideal. To avert this error in the future, we update these two weight vectors accordingly: $$w_y=w_y+f,$$ and $$w_{y\prime}=w_{y\prime} - f.$$

2) The One-vs-One (1v1) Mutli-class Perceptron

In this technique the perceptron maintains $S = (k * (k-1)) / 2$ weights vectors, one for each distinct pair of classes, each weight vector of the same dimension as the number of features. Every weight vector corresponding to $w_{(y, y')}$ can be thought of as a binary classifier between classes y and y'. When we come to an instance (f,y), assuming some ordering among the classes; $$w_{(y, y')} \cdot f > 0 \implies max(y, y')$$ is the class that gets a vote and $$w_{(y, y')} \cdot f \leq 0 \implies min(y, y')$$ is the class that gets a vote. While guessing the class of an unknown data sample we do S such votes and the class that receives the maximum votes is predicted, with ties settled arbitrarily.

Learning Algorithm

Here we need to analyse all class pairs separately; that is, for each distinct (y, y') pair, we consider only data points belonging to these two classes, and perform a binary perceptron algorithm like update (as taught in class) on them. (Note : No need to actually separate the training samples according to class pairs, you can do this in the same loop while iterating through all the data points).

Task 1: Implementing 1vr Perceptron (3 marks)

In this task, you have to implement the 1-vs-rest multi-class Perceptron classifier. Fill out code in the `train()` function at the location indicated in `perceptron1vr.py`. Using the addition, subtraction, and multiplication functionality of the `Counter` class in `util.py`, the perceptron updates should be relatively easy to code. Certain implementation issues have been taken care of for you in `perceptron1vr.py`, such as the following.

- Iterating over the training data.
- Setting up the `weights` data structure. This can be accessed using `self.weights` in the `train()` method.
- Predictions for each label/class are performed by a separate weight vector, as described above. Therefore, each legal label needs its own `Counter` of weights.

Run your code with the following command.

```
python dataClassifier.py -c 1vr -t 80000 -s 20000
```

This will print out a host of details, such as the classifier that is being trained, the training set size, if enhanced features are being used (more on this in Task 4), etc. After this, the classifier gets trained for a default of 3 iterations. `dataClassifier.py` would then print the accuracy of your model on the train and test data sets.

The `-t` option passed to the Perceptron training code specifies the number of training data points to read in from memory, while the `-s` option specifies the size of the test set (the train and test data sets are mutually independent). Since iterating over 100000 points may take some time, you can use 1000 data points instead while developing and testing your code. However, note that all our evaluations will involve train and test data sets with 100000 points.

Evaluation: Your classifier will be evaluated by for its accuracy on the test set after the Perceptron has been trained for the default 3 iterations. You will be awarded 3 marks if the accuracy exceeds 70%, otherwise 2 marks if accuracy exceeds 60%, otherwise 1 mark if accuracy exceeds 50%, otherwise 0 marks. You can run the autograder script to test your final implementation.

AutoGrader Script for this task is as follows.

```
python autograder.py -t 1
```

Task 2: Analysing the 1vr perceptron's performance (2 marks)

One of the problems with the perceptron is that its performance is sensitive to several practical details, such as how many iterations you train it for, the order you use for the training examples, and how many data points you use. The current code uses a default value of 3 training iterations. You can change the number of iterations for the perceptron with the `-i iterations` option. In practice, you would use the performance on the validation set to figure out when to stop training, but you don't need to implement this stopping criterion for this task.

Instead, you need to analyse and comment on how the test and train accuracy changes (1) as the total number of data points seen during training change, and (2) as the total size of the training set changes. See details below.

1. **Variation with number of training data points 'seen':** In this sub-task, you need to plot the train and test accuracy as increasing numbers of data points are 'seen' (that is, a point is examined to determine whether an update needs to be made to the Perceptron1vr, or the point is already correctly classified, and so no update is needed) by the classifier.

   You have been provided helper code for this purpose: the `train()` function in `perceptron1vr.py` writes `<examples seen>,<train and test accuracy>` as a comma-separated pair into the file `perceptron1Iterations.csv` and `perceptron1IterationsTrain.csv` 20 times in an iteration. The plotting script `createGraphIterations.gnuplot` uses this csv file to create the required plot and save it in a file by name `plot_iterations.png`. You can modify either of the two code files mentioned above to modify the plot being generated. 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.

   Below are commands to generate the required graph.

   - `python dataClassifier.py -c 1vr -t 8000 -s 2000 -v`
   - `gnuplot createGraphIterations.gnuplot`

2. **Variation with training set size in each iteration:** Here, you will see the influence of training set size on the accuracy of train and test set, when trained for the same number of iterations.

   Every time `dataClassifier.py` is run, it writes a comma-separated pair of numbers<training set size>,<accuracy>for the train and the test sets to files `perceptron1vr_train.csv` and `perceptron1vr_test.csv`. Use `createData.sh` (supplied in the zip file) to run the perceptron training on 100, 200, 300, ..., 1000 examples. Create a plot named `plot_training.png` by running `createGraphTraining.gnuplot`. Below are commands to generate the required graph.

   - `./createData.sh`
   - `gnuplot createGraphTraining.gnuplot`

   Append your observations and description of the plot obtained in the file **`answers.txt`** (to which you had already written in the previous sub-task). Additionally, answer the following question.

1. Imagine a point on the x axis with 0 training points: that is, a classifier that must make predictions based on no training data at all! How would such a classifier make predictions? On this data set, what would be the expected accuracy of such a classifier?

Note: The bash script to generate the data for the graph might take a long time to run. You are advised to proceed to subsequent tasks while the script is running.

Evaluation: Sub-tasks 1 and 2 will be evaluated for a total of 2 marks, with the plots and the corresponding explanations and answers all taken into consideration.

Task 3: Implementing 1vr Perceptron (4 marks)

Implementing the algorithm (3 marks)

In this task, you have to implement the One-vs-One multi-class Perceptron classifier. Here you can think of each weight vector as a binary classifier and so the updates to multiclass perceptron are just updates to multiple relevant binary perceptrons. Fill out code in the `train()` function at the location indicated in `perceptron1v1.py`. Using the addition, subtraction, and multiplication functionality of the `Counter` class in `util.py`, the perceptron updates should be relatively easy to code. Certain implementation issues have been taken care of for you in `perceptron1v1.py`, such as the following.

- Iterating over the training data.
- Predictions for each label/class are performed by a voting scheme, as described above. Therefore, each legal label pair needs its own `Counter` of weights.

Run your code with the following command.

```
python dataClassifier.py -c 1v1 -t 80000 -s 20000
```

Task 3.1 : Comparing the performances of perceptron1vr and perceptron1v1 (1 mark)

Run an experiment using only 800 data points for training while testing on 8000 data points (D1.2). Do this for both perceptron1vr and perceptron1v1. Use the following calls.

```
python dataClassifier.py -c 1vr -t 800 -s 8000
```

```
python dataClassifier.py -c 1v1 -t 800 -s 8000
```

Describe the result in the **`answers.txt`**. Also mention the test accuracies obtained while both the perceptron algorithms running on 80000 train and 20000 test, that is the full D1 data set. You need to compare the test accuracies acquired by the two algorithms for both the datasets and state and explain your observations.

Evaluation: Your classifier will be evaluated by for its accuracy on the test set (from D1) after the Perceptron has been trained for the default 3 iterations. You will be awarded 3 marks if the accuracy exceeds 75%, otherwise 2 marks if accuracy exceeds 65%, otherwise 1 mark if accuracy exceeds 55%, otherwise 0 marks. 1 mark is reserved for writing the analysis in answers.txt.

AutoGrader Script for this task is as follows.

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

Task 4: Feature Design (3 marks)

This task will require using the data set D2. It requires using the One-vs-rest classifier (Perceptron1vr) implemented in Task 1.

Building classifiers is only a small part of getting a good system working for a task. Indeed, the main difference between a good classification system and a bad one is usually not the classifier itself, but rather the quality of the features used. Run the Perceptron1vr algorithm implemented in Task 1 on the D2 data set using this command.

```
python dataClassifier.py -c 1vr -t 800 -s 200 -k 4 -d d2
```

So far, we have only used the simplest possible features: the identity of each pixel (being on/off). You will see a good accuracy (>90%) achieved. Your task is to use **at most 5 features** i.e. 5 float/int valued features and achieve as much accuracy as possible. You will need to extract more useful features from the data than the pixel values and use only them as features. The `EnhancedFeatureExtractorDigit()` in `dataClassifier.py` is your new playground. When analysing your classifiers' results, you should look at some of your errors and look for characteristics of the input that would give the classifier useful information about the label.

As a concrete illustration, consider the data you have used. In each training point (a inary matrix corresponding to an image), consider the number of separate, connected regions of white pixels. This quantity, although it does not vary across shapes, is an example of a feature that is not directly available to the classifier from the per-pixel information. Further you can add features that cumulatively describe all the per pixel values. You can also try analysing edges and corners.

If your feature extractor adds new features such as the quantity described above (think of others, too!), the classifier will be able exploit them. Note that some features may require non-trivial computation to extract, so write efficient and correct code. Add your new features for the shape data set (D2) in the `EnhancedFeatureExtractorDigit()` function.

We will test your classifier with the following command.

```
python dataClassifier.py -c 1vr -t 800 -s 200 -k 4 -d d2 -f
```

Evaluation: If your new features give you a test accuracy exceeding 85% using the command above, you will get 3 marks. Accuracy exceeding 70% will get 2 marks and accuracy more than 50% will get 1 mark

Note: Using comments in your code, briefly explain the working of your `EnhancedFeatureExtractorDigit()`.

AutoGrader Script for this task is as follows.

```
python autograder.py -t 4
```

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`** 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 `la1-rollno`, where `rollno` is your roll number (say 12345678). Tar and Gzip the directory to produce a single compressed file (say `la1-12345678.tar.gz`). It must contain the following files.

1. `perceptron1vr.py`
2. `perceptron1v1.py`
3. `answers.txt`
4. `dataClassifier.py`
5. `plot_iterations.png`
6. `plot_training.png`
7. `references.txt`

Submit this compressed file on Moodle, under Lab Assignment 1.