MPML REPORT

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Contents

Abstract

to be finished

1 Min-max algorithm

The min-max algorithm partitions the positive set and negative set into small parts, for example, the positive set is partitioned to n parts and the negative set to m parts. Then build n*m svm models between these parts. For each input, feed it to all the models, the result is:

$$predict[i][j], i \in positivelabel, j \in negativelabel$$

Then the predicted class of this input is:

$$max(min(predict[i][j], j \in negativelabel), i \in positivelabel)$$

This algorithm can improve the accuracy of classifier and avoid overfitting problem. However, the penalty is that min-max algorithm need more time to train models and predict the result. Another advantage is that it can be fully parallelized easily, and each single model involves smaller data set. So it may even speed up the training phase in some cases.

The most important problem is which partition function to choose. Usually a partition function should partition the data into proper number of parts, and have some structural reasons which seperate similar data into the same set. In this experiment I choose two different partition function to compare, the first one is partitioning randomly and the second one is partition by the first two letter in the input's first label.

2 Parallelization

Because of the GIL in python interpreter, multi-thread model do not help in this experiment. The trainning phase and the testing phase is parallelized using multiprocessing module. In trainning phase, each model is trained by a single process. In testing phase, batch predicting is used and each process calculate the result of exactly one model.

The multi-process model is much safer than multi-thread model, in this case I just need to join child process and get the result. However, the efficiency of multi-process is even worse than serialized version in the beginning.

The first problem is fork() function will copy all the state of current program, which copied the training data for multiple times. To deal with this problem, I write each part of data set into a single file and read them in each child process so that I can release the space of data set before fork().

Another problem is the big cost of frequent context switch. So I use Pool.map method of multiprocessing module which runs exactly 4 processes in my 4-kernal machine. It also reduces the space cost of the dead processes.

With these technich, the parallelized min-max algorithm is more than 2 times faster compare with the serialized version. The difference between multi-process and multi-thread is the big cost of message exchanging which involves data copy in multi-process. For further optimization, using c to write the code or call python in c code would be a good direction.

3 Implementation

The python version is implemented with MPI,the source code is partitioned into several parts via its functions. I will introduce the main structure of this project in the following.

3.1 usage

To test a classifier, configure the algorithm in *settings.py*. If min-max net algorithm is used, specify the partition function in *settings.py*, then run this command:

```
$ cd src/
$ python3 main.py
```

In addition,if you want to run with the origin data, set PARSE_DATA = True so that the program will parse the origin data into .pickle files. The time of parsing do not count in total time in timer class as you only need to parse the data for just one time. Other advanced options can be found in the folloing part.

When all the algorithm have been tested, you can draw the ROC graph by *drawroc.py*. Run this command to draw ROC graph and calc AUC value:

```
$ python3 drawroc.py
```

3.2 structure

All the source code can be found in src/ folder. src/core/ stores the main part of brute liblinear, serialized min-max and paralleled min-max algorithm. src/data/ stores the training data, testing data and all the template .pickle files. src/models/ stores all the svm models. src/tools/ stores many tool function for this project. src/timer/ contains timer class. src/utils/ contains util functions. src/settings.py contains default settings. src/main.py is the main program. src/drawroc.py draw ROC graphs via the result file in src/data/ folder.

3.3 settings.py

The *settings.py* file contains default settings of this project, containing default algorithm, partition function in min-max algorithm,some constant and some folder/file name. As there are no time to implement a parser, you must edit *settings.py* to configure the algorithm.

To start with, set the value of ALGORITHM to specify which kind of algorithm you want and then set the value of PARTITION_ALGORITHM to choose partition function(labeled of randomed).

If you want to use post models for debugging, set MEMORIZE = True. If you want to test the program in a smaller data set, set TRAIN_DATA to your desired item numbers greater than 0. If you want to patition the items into a different number of sets in random labeled min-max net algorithm, change the value of MAX_CLASS to the max number of sets.

Other settings are seldom used and you can learn about their function by reading the source codes.

3.4 utils and tools

The utils module comes from a repo in github, it mainly contains functional programming style util functions such as partition, mapValue and mapv. A cd class is also contained to ensure safe dictory switch.

src/tools stores the tools specificly designed for this project. *partition.py* contains partition functions used to partition data into different sets in min-max algorithm. *dataIO.py* implements the IO instruction with files. *parseData.py* parses the origin data into a hash-map in python, and dump it to a .pickle file. The main program will use the .pickle file directly so this module will not be called in main program. *tools.py* defines getModel, predictResult ,compareResult and metaNameFunc which will be used in all the three algorithms.

3.5 drawroc.py

drawroc.py use matplotlib.pyplot module to draw the ROC graph. First it reads the result file of different algorithms, then call pyplot to draw the ROC graph. Also the AUC value of the result is also calculated and printed to the screen.

3.6 timer

timer.py uses time module to implement a multi-record timer. Different record are stored in a hash-map and distinguished by its name. The start and end method can start/end the timing a specific record. Also an add method is provided to add a value to a record.

3.7 core

The core module contains the main part of the program. *brute.py* use liblinear directly to solve the origin problem. *minmax.py* defines the abstraction of min-max algorithm and implements the serialized version of this algorithm. *multiProc.py* implements the parallelized version of min-max algorithm.

All the algorithms contains a training phase and a testing phase, the time of the two phases is rbecorded by the timer. The total time contains the time cost of two phases and loading data.

4 Trainning Result

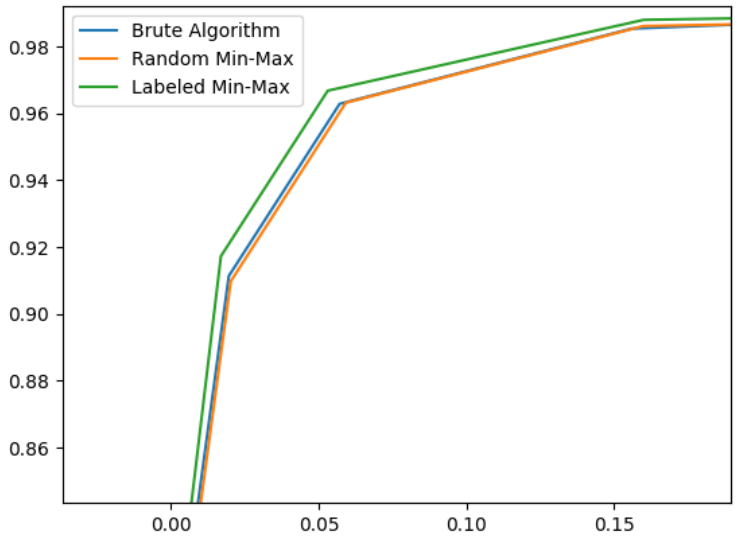
The trainning result is as following:

No.	Algorithm	paralleled?	Time/s	Accuracy	F1 value	AUC value
1	brute svm	\	34.04	96.37167%	0.92404	0.48782
2	random min-max	no	305.47	96.26846%	0.92194	\
3	random min-max	yes	140.08	96.26846%	0.92184	0.48307
4	labeled min-max	no	204.35	96.71042%	0.93101	\
5	labeled min-max	yes	204.35	96.69719%	0.93074	0.48567

The random min-max algorithm separate the input data into 5 parts randomly(5*5 models). The labeled min-max seperate the input data via the first two letters(4*12 models).

The total contains the time of load data, save model and other IO operations. Parsing is finished before the program runs.

The ROC Graph is as following:



The time cost between serialized min-max and parallelized min-max is:

No.	Parallelized?	Algorithm	Trainning time	Testing time	Total time
1	Yes	labeled	59.37346 s	144.54046 s	203.93383 s
2	No	labeled	115.96271 s	371.83840 s	489.00508 s
3	Yes	random	54.49303 s	84.16756 s	138.69087 s
4	No	random	103.98813 s	200.19163 s	305.47026 s

Test environment is Ubuntu, 4 kernal. Python version is 3.5.

5 Analysis