A Novel Method for Tuning Configuration Parameters of Spark Based on Machine Learning

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Contribution

--proposed a novel method for tuning configuration parameter of spark based on machine learning

--established a model based on binary classification and multi classification

--several common machine learning algorithms for configuration parameter tuning are explored based on the model

--Decision Tree (C5.0) has good accuracy and computational performance across diverse workloads for binary classification and multi-classification

--An average of 36% performance improvement can be got with the proposed method. Moreover, with the increase of input data, the effect of performance improvement is more obvious

The Framework of Performance Modeling

--use the execution time of Spark application to represent the performance

--goal: compare the performance improvement under a given set of values of configuration parameters with the default value of these parameters

--divide the problem solving process into two steps

The Framework of Performance Modeling

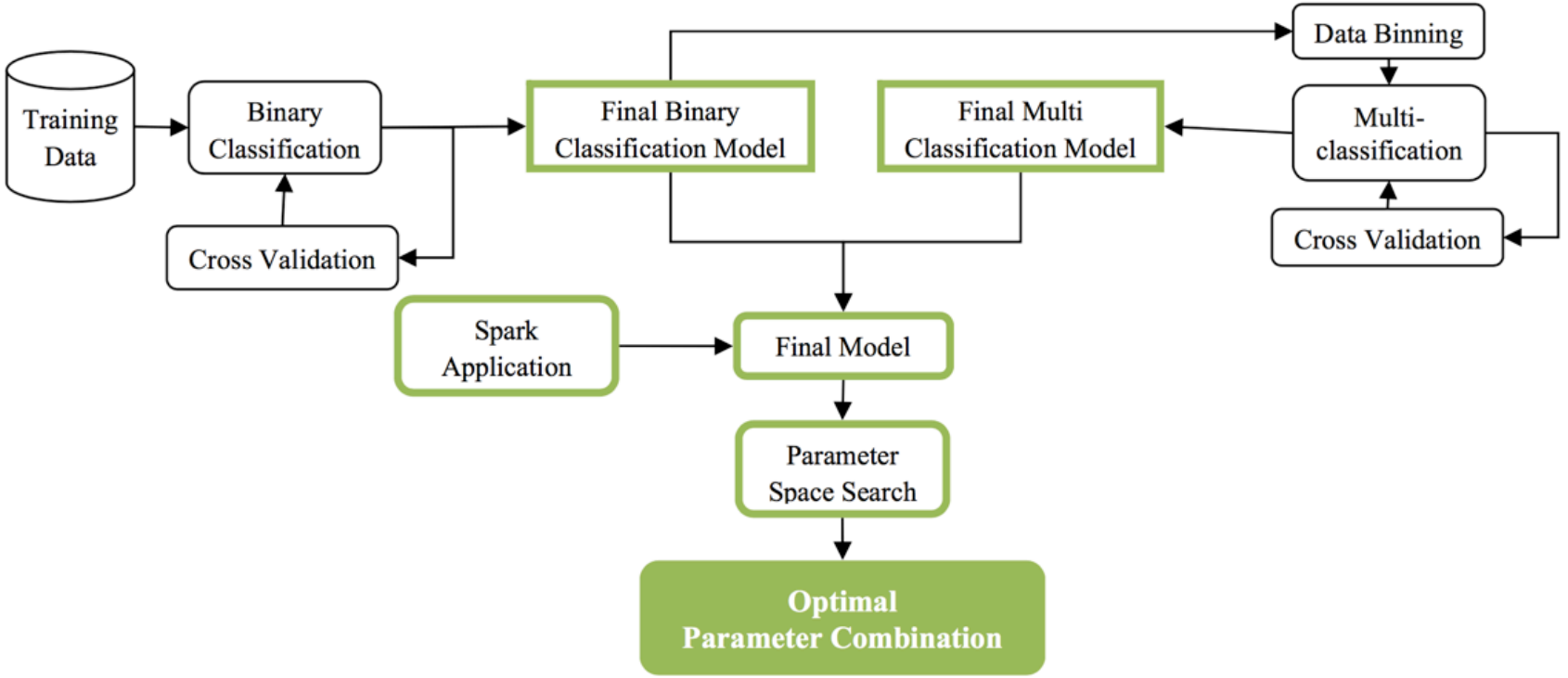


Figure 2. The framework of performance model and optimization method for Spark

--Firstly, a binary classification model is built, and the execution time of Spark application under a given set of parameters is predicted, if it is shorter than the the execution time under the default parameters, then the label of the category is set to 1, else 0

The Framework of Performance Modeling

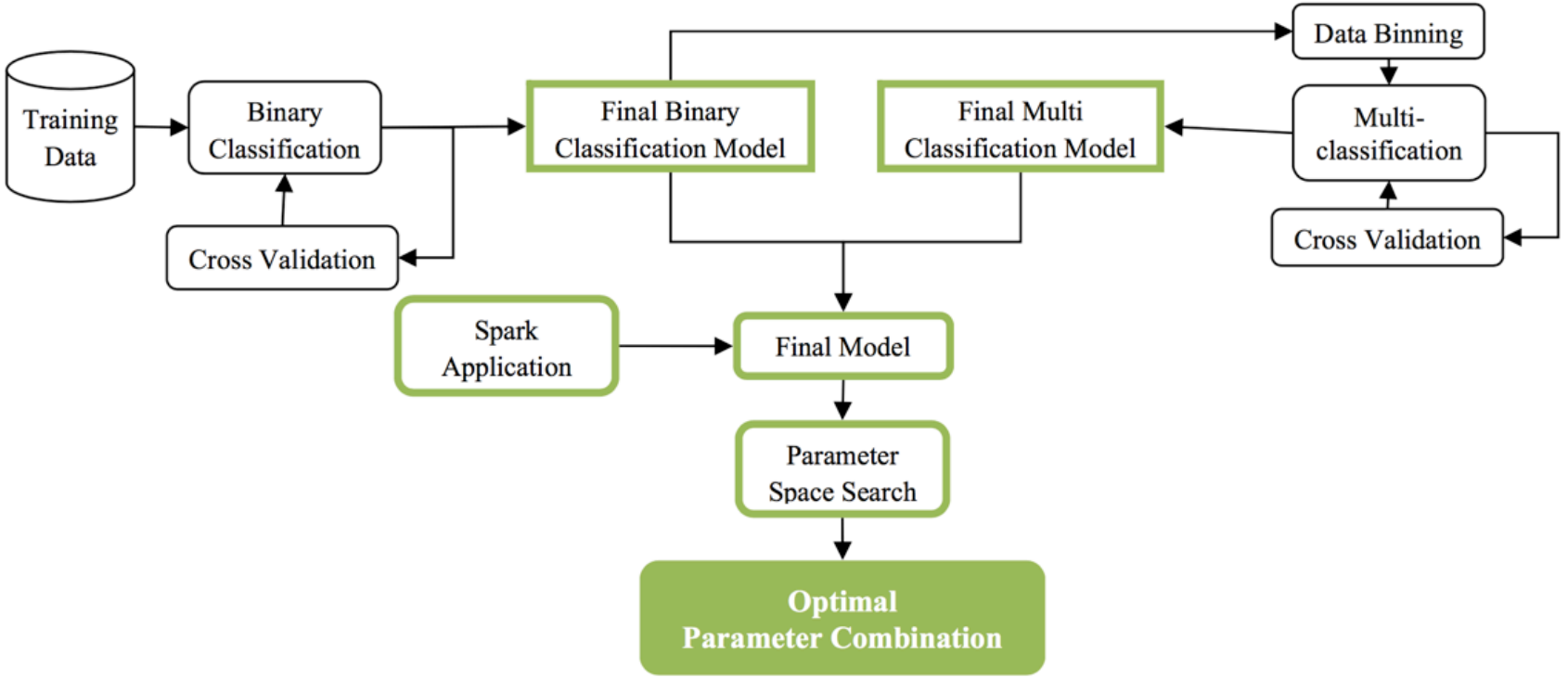


Figure 2. The framework of performance model and optimization method for Spark

--Secondly, a multi- classification model is built. The data labeled 1 is split into some bins according to the percentage of execution time reduction relative to the default parameters. For example, the data is split into 5 bins, and their execution times decrease by 5%, 10%, 15%, 20%, and 25% relative to the default parameters, which means that the data is divided into 5 categories, and then a multi-classification model can be trained according to the 5 categories

Parameter Selection

TABLE I. PARAMETERS THAT WE HAVE USED IN OUR PERFORMANCE MODELS

Parameter	Description	Default	Rules of Thumb
spark.driver.cores	Number of cores to use for the driver process	1	1--8
spark.driver.memory	Amount of memory to use for the driver process	1g	1g—4g
spark.executor.cores	Number of cores to use for the executor process	1	10-40
spark.executor.memory	Amount of memory to use per executor process	1g	2g--8g
spark.reducer.maxSizeInFlight	Maximum size of map outputs to fetch simultaneously from each reduce task	48m	24m--96m
spark.shuffle.manager	Implementation to use for shuffling data	sort	sort/hash
spark.shuffle.compress	Whether to compress map output files	true	true/false
spark.shuffle.spill.compress	Whether to compress data spilled during shuffles	true	true/false
spark.broadcast.compress	Whether to compress broadcast variables before sending them	true	true/false
spark.io.compression.codec	The codec used to compress internal data	Snappy	lz4/lzf/snappy
spark.broadcast.blockSize	Size of each piece of a block for TorrentBroadcastFactory	0.2	0.1-0.3
spark.default.parallelism	Default number of partitions in RDDs returned by transformations like join, reduceByKey and parallelize when not set by user.	0.6	0.4-0.8
spark.speculation	Whether to perform speculative execution of tasks.	4m	2-8m
InputDataSize	The size of the input dataset	NULL	NULL

-- The first thirteen parameters are configuration parameters of Spark and the last one is the size of input data.
-- the ‘default’ column lists the default value of each parameter
-- the ‘rules of thumb’ column lists the values of each parameter that the industry recommends

Data Collection

-- Four kinds of typical workloads from BigDataBench are selected to build performance model, including Sort, Wordcount, Grep and NavieBayes

-- which parameter values should explore while collecting the training data
  -- exhaustive search over different small subsets of the parameter space (exploring a specific range of parameter values)
  -- random exploration that picks parameter values uniformly random from different range of values are used while collecting data
  -- combination of these two approaches
  -- A parameter list of 500 records for each workload is generated

-- the workloads are executed three times for every parameter configuration, which results in about 1500 training points for each workload

Model Selection

--Decision Tree

--SVM

-- Logistic regression

-- Artificial neuron network

Parameter Space Search

-- After getting the final model, we can use it to predict the execution time of Spark application in a given set of parameters

-- we cannot penetrate the whole parameter space

-- an optimized search algorithm to reduce the search space should be used –Recursive Random Search

-- RRS algorithm can provide probabilistic guarantees on how close the searching it finds is to the optimal parameter combination

Evaluation Metrics

-- computational performance
  -- the time for building the model and the time for making a single prediction using the model are evaluated

-- prediction accuracy

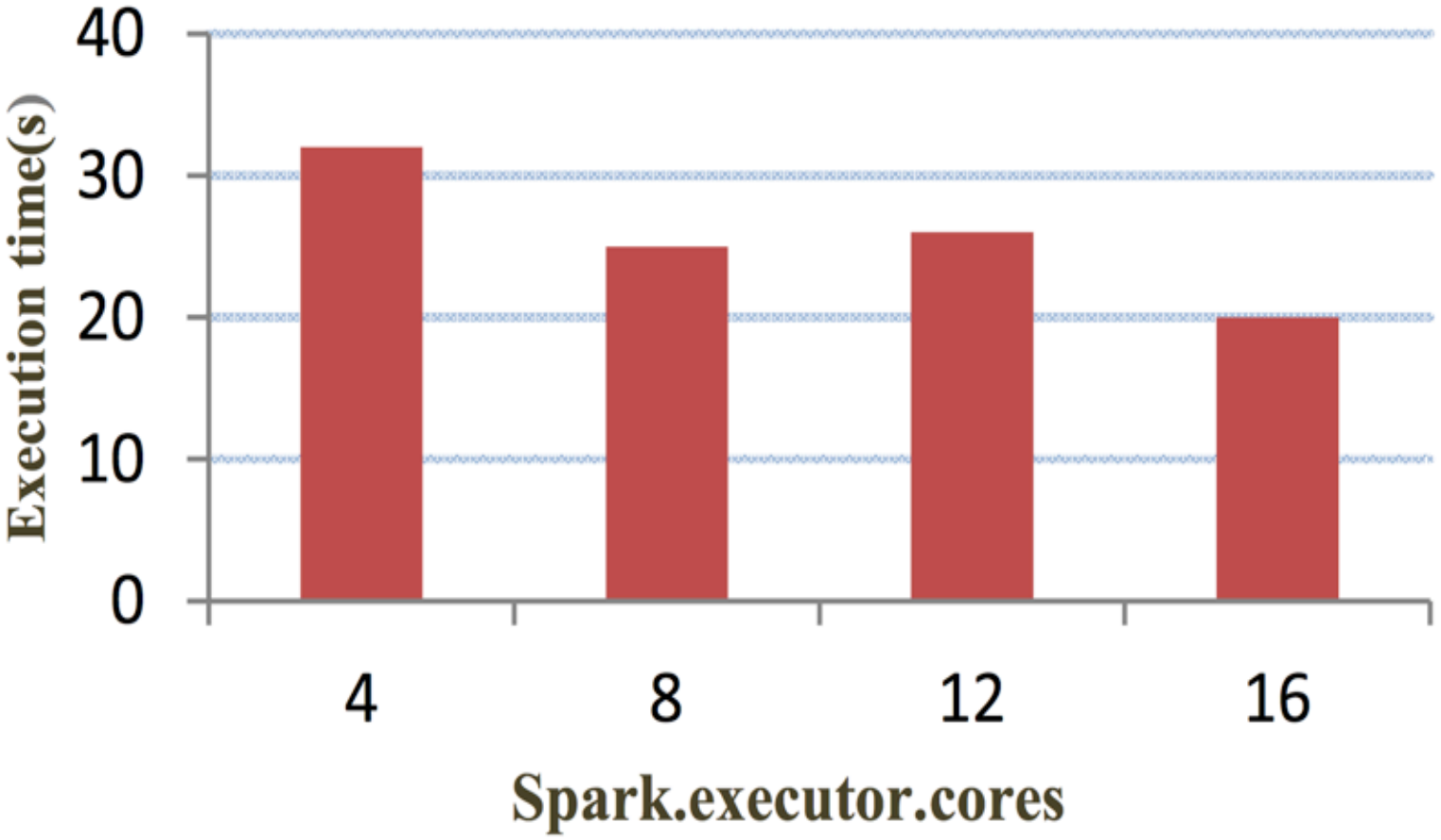


Figure 3. The execution time with different spark.executor.cores

-- workload is the WordCount in BigDataBench with 5GB input data on the 4-node IBM cluster

-- the execution times change a lot under different values of spark.executor.cores

-- the maximum change rate of execution time is 37%

Experiments--Necessity and Effectivity of Tuning Configuration Parameter of Spark

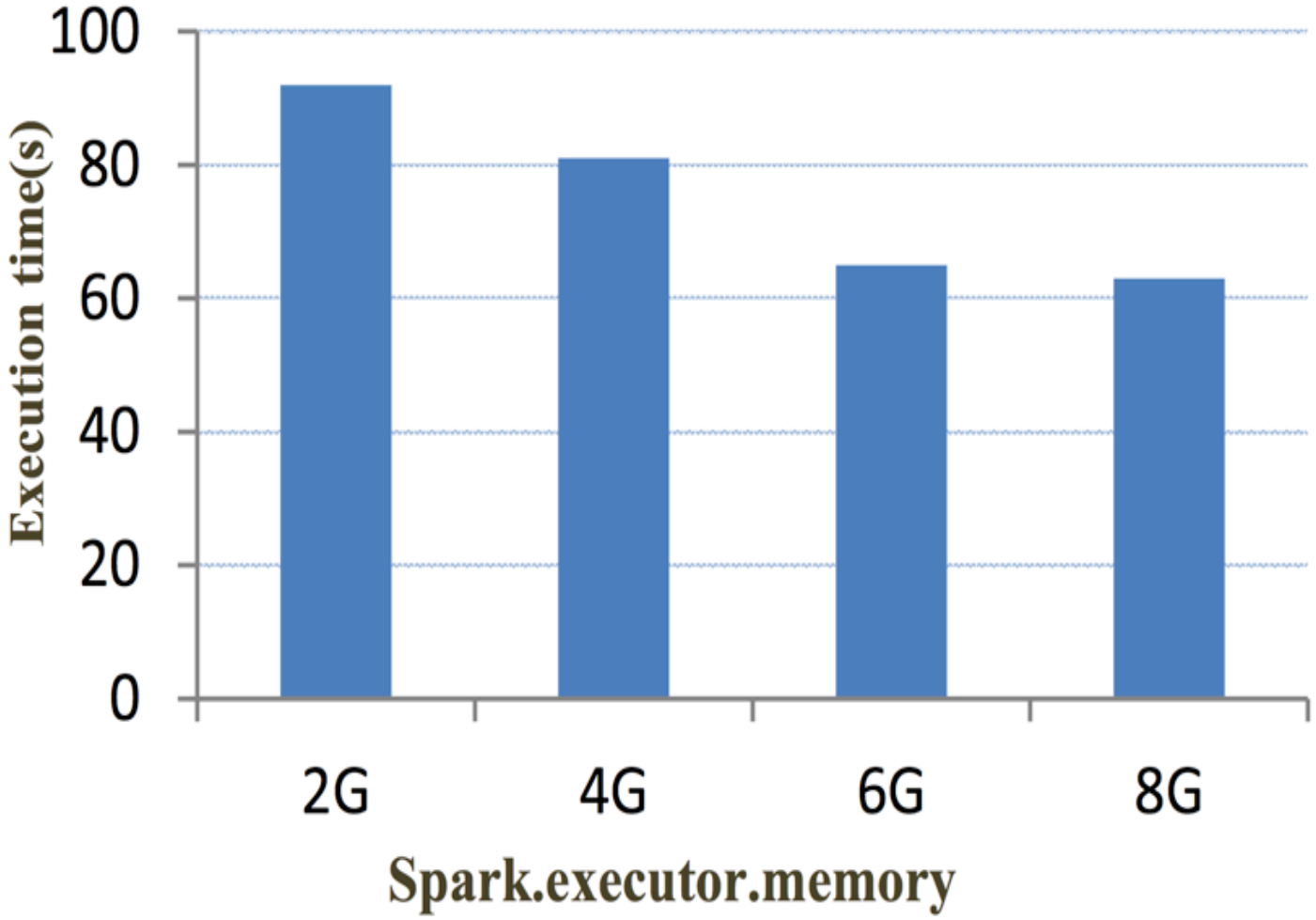


Figure 4. The execution time with different spark.executor..memory

-- The workload is the Grep in BigDataBench with 10GB input data on the 4-node IBM cluster

-- the execution times change a lot under different values of spark.executor.memory

-- the maximum change rate of execution time is 29%

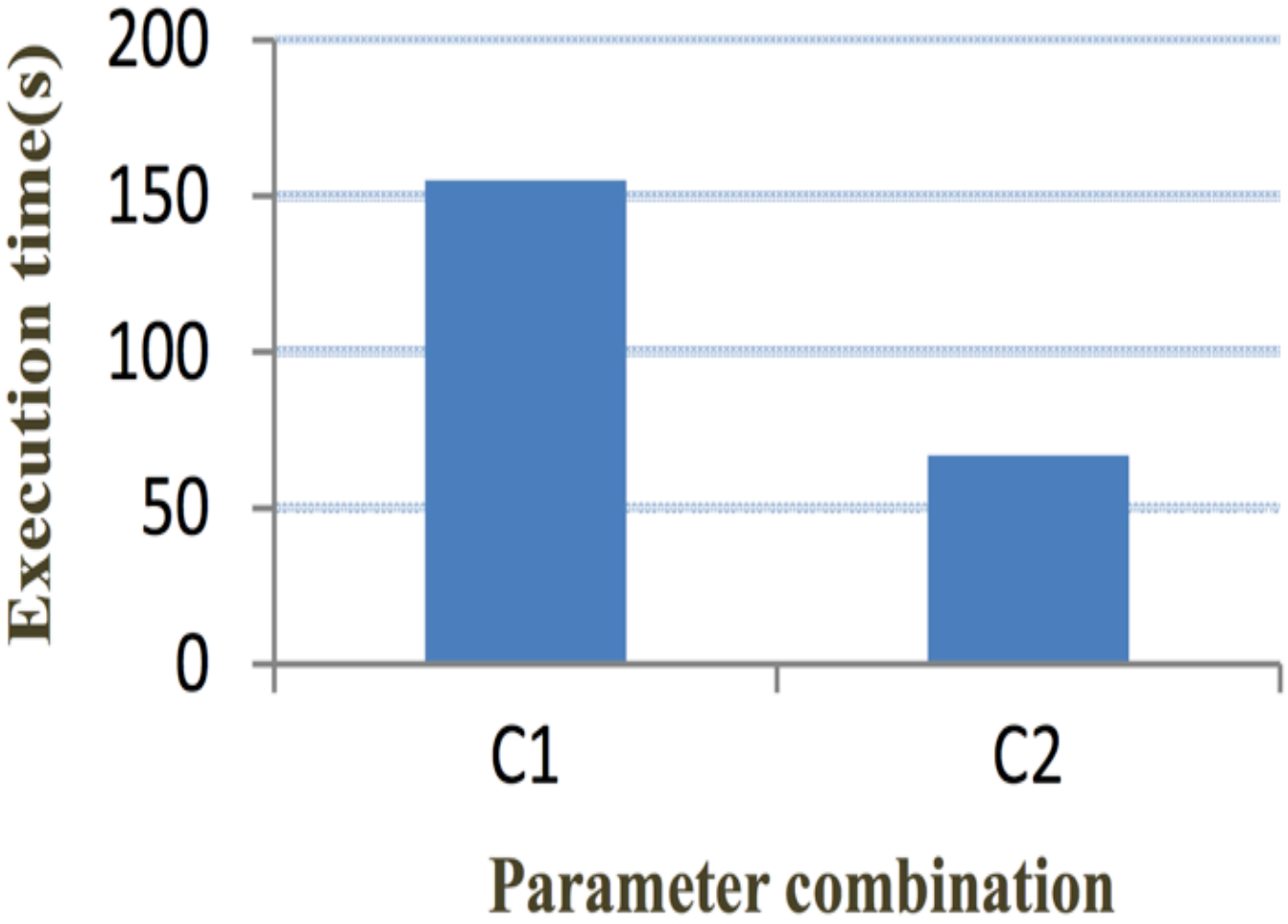


Figure 5. The execution time with two sets of parameters

-- First 13 parameters in Table I are selected and combined as parameter set C

-- *C1*=[*4,1g,8,4g,96m,sort,false,false,false,lz4,8m,100,true*]
-- *C2*=[*2,1g,16,2g,24m,hash,true,false,false,lzf,8m,110,true*]

-- workload is the Sort in BigDataBench with 1GB input data on the 4-node IBM cluster

-- tuning only a small number of parameters can reduce the execution time by half

Experiments--Evaluation of accuracy and computational performance of the models

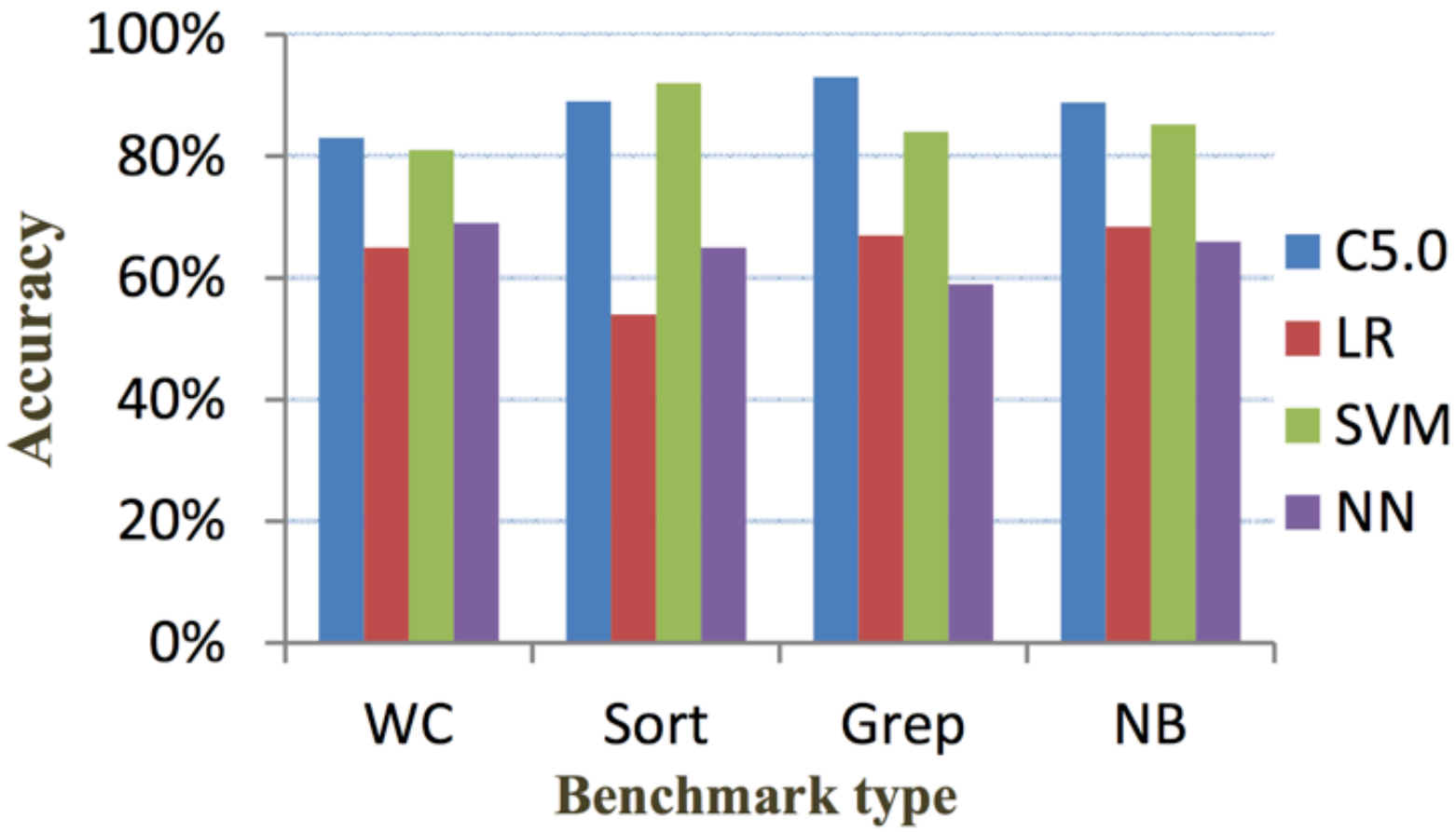
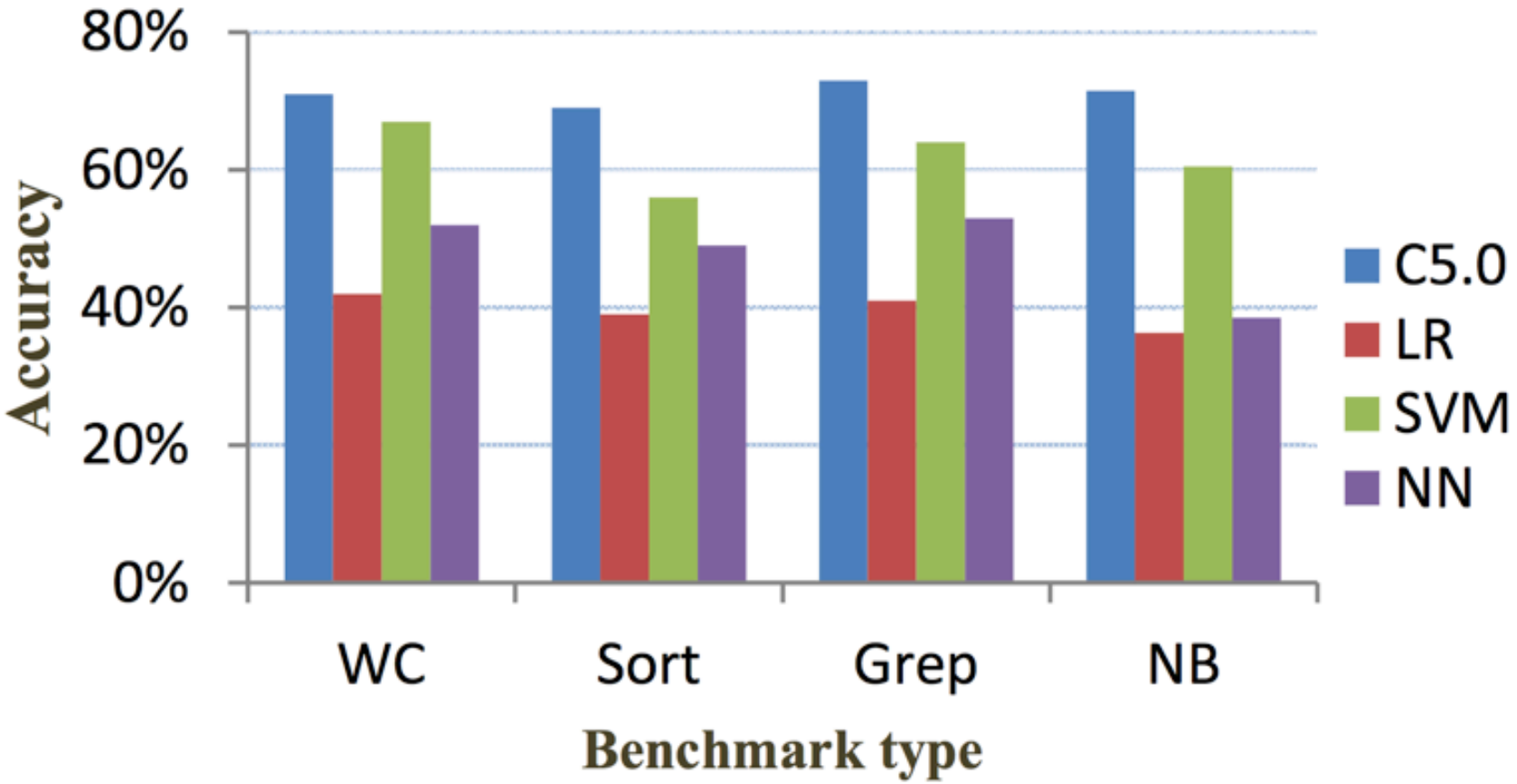


Figure 6. The accuracy of the models for Binary-classification

-- C5.0 and SVM have better accuracy on 4 kinds of benchmarks than other models

Experiments--Evaluation of accuracy and computational performance of the models



--C5.0 and SVM have better accuracy on 4 kinds of benchmarks than other models

Figure 7. The accuracy of the models for Multi-classification

Experiments--Evaluation of accuracy and computational performance of the models

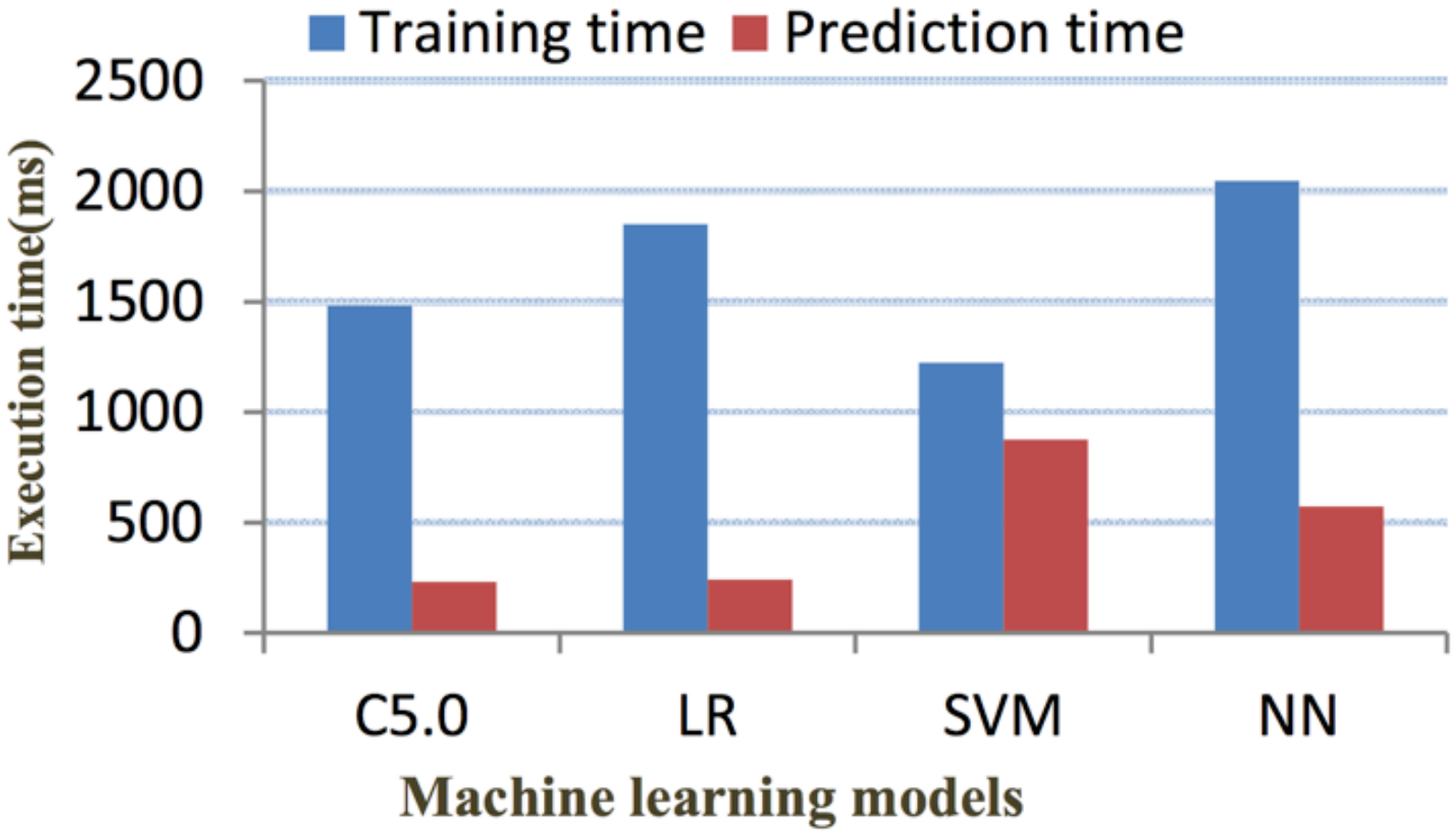


Figure 8. The computational performance of models

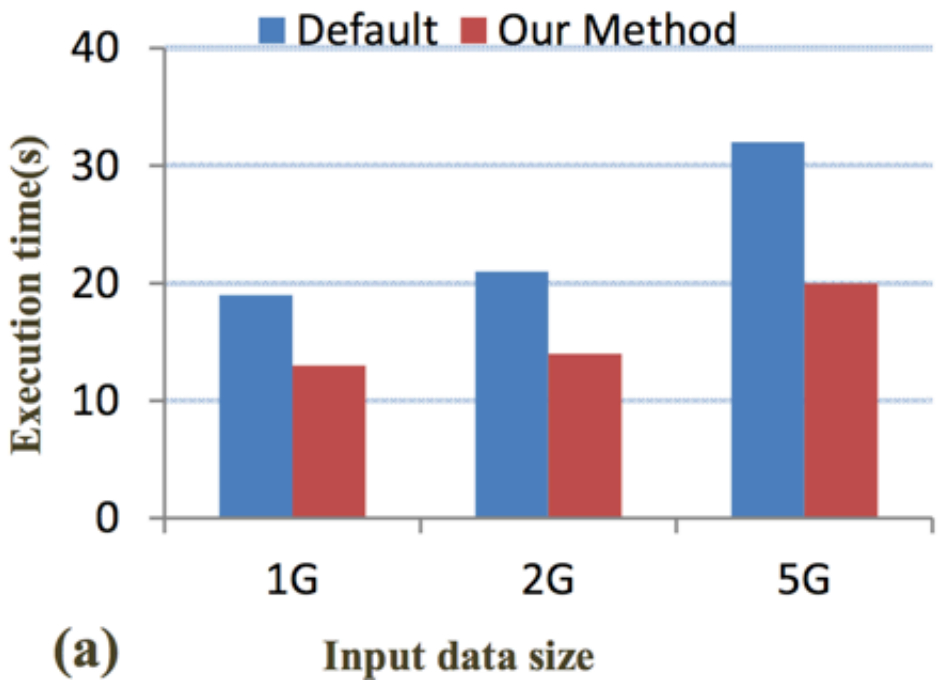
--training/ prediction time in the figure represents the time required by the model to train/prediction 1000 samples

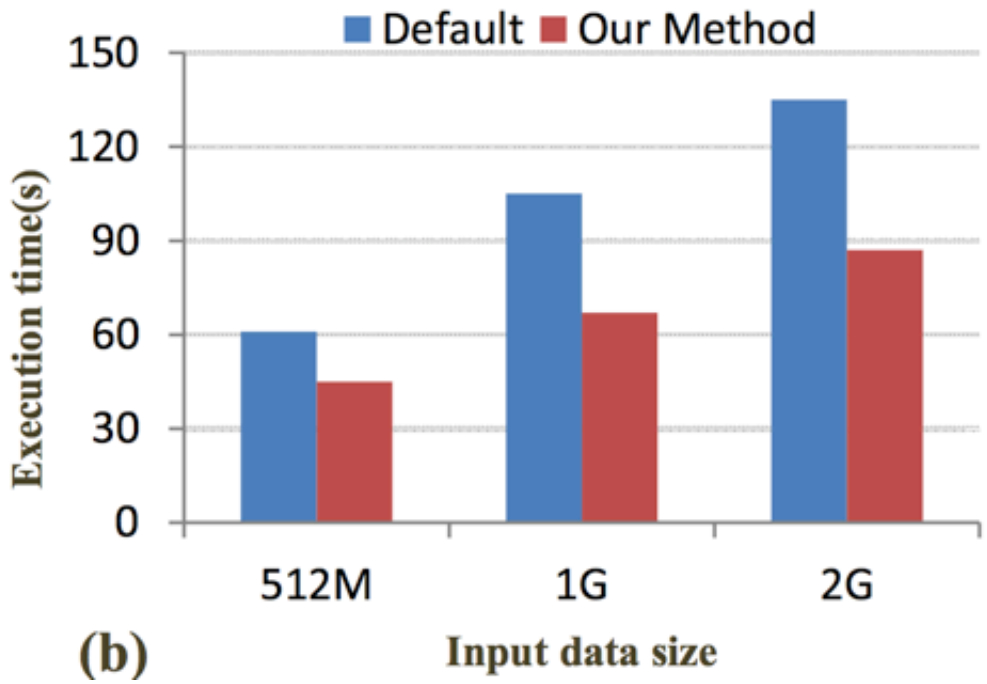
--SVM has the shortest training time, and C5.0 also has a shorter training time

--C5.0 and LR has shorter predict time than other models

--C5.0 has a greater advantage relative to other models in computational performance

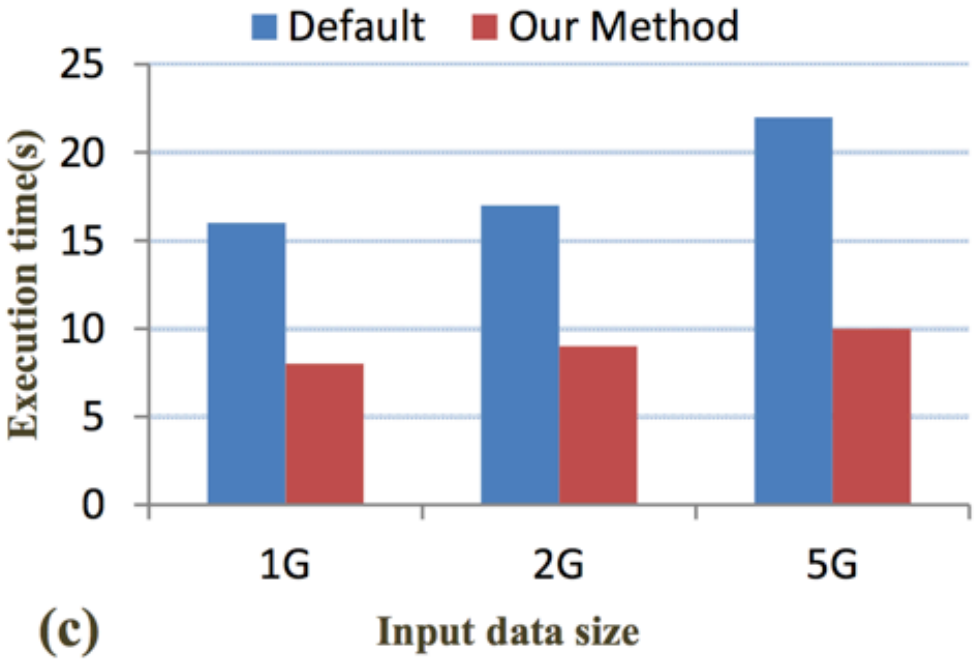
--Conclusion:C5.0 has a better performance both in accuracy and computational performance for binary-classification and multi-classification

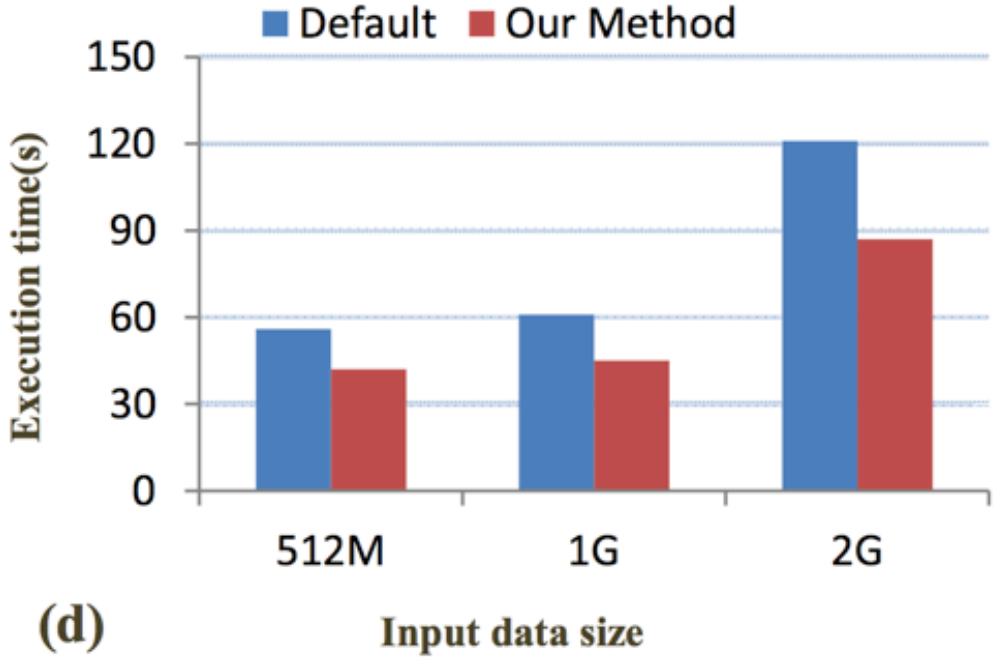




--(a) shows optimization effect of the WordCount benchmark
-- the proposed method has 31% performance gain when the input data is 1G and 38% performance gain when the input data is 5G. On average, the proposed method has a performance gain of 34%

--(b) shows optimization effect of Sort benchmark
-- method has maximum performance improvement of 36% and average performance improvement of 33%





--(c) shows optimization effect of Grep benchmark
-- method has maximum performance improvement of 55% and average performance improvement of 51%

--(d) shows optimization effect of NavieBayes benchmark
--method has maximum performance improvement of 28% and average performance improvement of 26%

--Conclusion: model has a significant performance improvement over the default parameters with the average improvement of nearly 36%. With the increase of input data, the effect of performance improvement is more obvious

Future Work

--They will conduct further research on parameter selection in order to select more suitable parameters

--They will also consider more aspects affecting on the performance, such as the resource competition between the jobs, theme fluctuation of network bandwidth and so on