Characterizing Distributed Machine Learning Workloads - Technical Report

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1 Introduction

This document presents a technical report of the distributed machine learning (DML) workloads characterization work, presented in the paper entitled *Characterizing Distributed Machine Learning Workloads*. The rest of the document is organized as follows. In §2, we provide the experimental setup of our characterization methodology, along to its key elements, including the DML workloads we utilize, the configuration parameters we consider, and the metrics we gather. In §3 we provide statistical characteristics of the collected workloads traces and suggest ways to use them. In §4, we present the results of tuning two types of configuration parameters, namely the distributed platform parameters and the leanring models hyper-parameters, and this for the different workloads. We conclude our technical report in §5.

2 Trace Collection Methodology

In the following, we start by describing the experimental setup of our characterization study. Next, we present the DML workloads that we utilize to collect our traces. We also provide details about our exploration methodology of the configuration parameters space, to understand the impact of different parameters on the workloads' performance. Finally, we provide the collected metrics.

2.1 Experimental setup

We use Spark 2.4.0 as distributed computing platform and HDFS 2.7.7 as distributed file system. The used DML library is MLlib (v2.4.0) [20] or BigDL (v2.4.0) [9]. We conduct our experiments on two clusters as described below.
Cluster 1. Cluster 1 is a 4-nodes cluster equipped with a quad-socket Intel E3-1275 CPU processor, 8 cores per CPU, 64 GiB of RAM, 480 GB SSD drives, on a switched 1 Gbps Ethernet LAN, running Ubuntu Linux 16.04.1 LTS.
Cluster 2. To consider more hardware diversity and run bigger workloads, we also deploy a 24-nodes cluster, dual-socket 8 core Intel Xeon E5-2630 CPU,

Table 1. Learning datasets

CC	Dataset	Description	#Records	#Features	Size
	DDF (Drive-face)	Images sequences of subjects while driving.	606	6,400	19.9 MB
	DGS (Drift)	Measurements from 16 chemical sensors utilized in a discrimination task of 6 gases.	13,910	129	40.3 MB
	DHG (Higgs)	A collection of kinematic measures to detect signal processes which produce Higgs bosons.	11,000,000	28	7.5 GB
	DN (News20)	Messages collected from 20 different newsgroups.	118,845	2	68.7 MB
	DFM (Fashion MNIST)	Images of fashion articles, associated with labels from 10 classes.	700,000	784	54.9 MB
	DM (MNIST)	Handwritten digit images for ML research.	70,000	784	52.4 MB

128 GB RAM, 600 GB HDD, 2× 10 Gbps Ethernet, running Debian GNU/Linux 9.7.

There are several reasons behind our choice of using CPU-only clusters. First, CPU clusters do not have the memory constraints of GPU clusters and can handle larger models [16, 26]. Second, recent works show that CPUs are still in the competition and may even yield better performance than GPUs for deep learning [7]. Finally, we are interested in the relative impact of different configuration strategies and not in the absolute performance that may be obtained. If GPUs may accelerate training time supporting high parallelisation [12], we focus in our work on how different parallelisation settings, together with other platform and hyper- parameters, impact global DML performance.

2.2 DML Workloads

ML Datasets. We consider six commonly used and publicly available datasets [1, 27, 10, 11, 25, 5] shown in Table 1 (the CC columns in Tables 1 and 2 indicate the color codes used later in the graphs). We have chosen datasets to differ in terms of content type (*e.g.*, text, images), number of records, number of features and total size.

In our experiments, we use random split to define the training and inference sets. 80% of each dataset are used for model training and the remaining 20% are dedicated to inference.

ML Methods. We test 13 state-of-art ML methods commonly used by data scientists including 9 MLlib's methods and 4 BigDL's methods (see Table 2). They MLlib methods implement clustering, classification or regression and are based on different learning methods such as gradient descent, decision trees and neural networks. The deep neural networks have the following architectures.include a CNN consisting of 9 layers, a GRU with 7 layers, a LENET5 (a specific CNN for the MNIST dataset) with 5 layers and a LSTM with 7 layers.

In the rest of the paper, the names of the workloads are composed of the name of the dataset followed by the name of the learning method. For example,

Table 2. Learning methods

Library	Category	ML Method	CC
MLlib	Clustering	KM (K-Means)	
		BKM (Bisecting K-Means)	
		GMM (Gaussian Mixture Model)	
	Classification	DT (Decision Tree)	
		MLP (Multilayer Perceptron)	
		BLR (Binomial Logistic Regression)	
	Regression	LR (Linear Regression)	
		RFR (Random Forest Regressor)	
		GBT (Gradient-Boosted Tree)	
BigDL	Classification	CNN (Convolutional Neural Network)	
		GRU (Gated Recurrent Unit)	
		LENET5 (Convolutional Neural Network)	
		LSTM (Long Short-Term Memory)	

for the `DDF` dataset and the clustering methods we have the `DDF-KM`, `DDF-BKM` and `DDF-GMM` workloads.

2.3 Parameter Settings

In our experiments, we deploy each workload (*i.e.*, dataset and ML method) on the corresponding DML environment (*i.e.*, MLlib or BigDL on a Spark cluster). For each deployed workload, we consider default values of hyper-parameters, default Spark platform parameters, variations for hyper-parameters and variations for different of Spark parameters. Each experiment is replicated three times, which is enough due to low variations in data, as shown by the confidence intervals in our plots.

Hyper-parameters. Based on previous works [13, 24, 23], we choose hyper-parameters that have a high impact on performance in terms of execution time and accuracy. These include the maximum depth of tree-based algorithms, the maximum number of iterations to reach model convergence and the learning rate and batch size of deep neural networks. More details can be found in Table 3.

Platform Parameters. We leverage existing studies [19, 4] that evaluate which Spark parameters affect performance most. These include scheduling, data transfers, data storage and representation, parallelisation and memory management. A detailed description of the used configuration parameters and the used experimental values are given in Table 4.

Most Spark parameters are left to their default values, except for executor memory; we changed the value from the default 1 GiB to 5 GiB to avoid out-of-memory issues. We used the same configuration values of Spark platform parameters for both MLlib and BigDL, except for executor configurations for BigDL. The configurations respect the constraints according to which the defined batch size has to be divisible by the total number of cores (*i.e.*, number of executors and the nomber of cores per executor are defined accordingly).

Table 3. Hyper-parameters

Hyper-parameter	Description	Values	MLlib / BigDL method
maxIter	Maximum number of iterations to achieve convergence.	5, 10, 15, 20, 50, 100	BLR, MLP, BKM, KM, GMM, GBT, LR, CNN, GRU, LSTM, LENET
maxBins	Number of classes for the discretization of continuous variables	4, 16, 32, 48	DT, GBT, RFR
maxDepth	Maximum depth of decision trees before convergence	5, 10, 15, 20	DT, RFR, GBT
tol	Convergence threshold for stopping the algorithm	0.000001, 0.0001, 0.01, 0.1	KM, GMM, MLP, BLR, LR
numTrees	The number of decision trees built	10, 20, 50, 100, 150	RFR
stepSize	Model learning rate	0.003, 0.03, 0.3	GBT, MLP, CNN, GRU, LSTM, LENET
blockSize	Batch size	32, 128, 256, 512, 1024	MLP, CNN, GRU, LSTM, LENET

2.4 Characterization Metrics

We introduce here the workloads' characterization metrics at the application, platform and infrastructure level. The complete list of collected metrics is provided in Table 5.

Application-level Metrics. Application-level metrics capture different aspects related to DML applications, including quality of the underlying model, execution times, throughput and costs. The quality of a classification model is typically measured through testing accuracy. The *testing accuracy* measures how well the trained model can be generalized to unseen data called test data. Some methods such as clustering algorithms (*e.g.*, K-Means) use the silhouette metric to evaluate the similarity of an object to its own cluster's objects. Other metrics used with regression algorithms include R-squared (R^2), root mean squared error (RMSE) and mean absolute error (MAE).

When it comes to execution time, the *training duration* is given by the training time in seconds. We normalize the *training duration* based on the number of records and report the training duration per thousand records. We report the *inference execution time* in the form of *inference throughput* which gives the number of requests processed per second (reqs/s).

Platform-level Metrics. We use *SparkMeasure* [2] to collect metrics from the Spark cluster. The reported metrics, exposed by the *TaskMetrics* class, include: *(1)* task duration (ms) which corresponds to the total time to perform the task; *(2)* task deserialization time (ms) which corresponds to the time spent to deserialize a given task; *(3)* shuffle time (ms), *i.e.*, the time spent by tasks waiting for data to become available from remote machines; and *(4)* JVM garbage collection time (ms).

Infrastructure-level Metrics. From each cluster node, we collect CPU usage (from `/proc/stat`), the memory usage (from `/proc/meminfo`), the network traffic (using `/proc/net/netstat` and filtering sent/received bytes) and the energy consumption. We collect power measurements every second via the processor counter monitor API [21].

Table 4. Spark platform parameters

Configuration aspect	Spark platform parameters	Description	Values
Parallel computing	EXEC_NUM (executor.instances)	Number of executors	MLlib: 1, 2, 3, 4, 5, 6, 7, 8, 12, 48, 72, 96; BigDL: 1, 2, 4
	EXEC_COR (executor.cores)	Number of cores per executor	MLlib: 1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 16; BigDL: 1, 2, 4, 8
Memory management	EXEC_MEM (executor.memory)	Amount of memory per executor	MLlib: 5 GB, 10 GB, 15 GB, 20 GB, 25 GB, 30 GB., 50 GB., 70 GB., 100 GB.; BigDL: 1 GB, 4 GB, 8 GB, 16 GB, 24 GB, 32 GB
	MAX_SIZ_INF (reducer.maxSizeInFlight)	Maximum size of map outputs to fetch simultaneously from reduce tasks	12 MB, 48 MB, 72 MB, 128 MB, 256 MB, 512 MB
	PD_BUFS (shuffle.io.preferDirectBufs)	Must use off-heap buffers to reduce garbage collection during data transfer	true, false
	STR_MEM (storage.memoryFraction)	Fraction of Java heap to use for Spark's memory cache	10%, 20%, 40%, 60%, 80%
Data compression	COMP_CODEC (io.compression.codec)	Codec to compress internal data such as RDD partitions, shuffle outputs, *etc.*	snappy, lz4
	RDD_COMP (rdd.compress)	Must compress serialized RDD partitions	true, false
	SHF_SPL_COMP (shuffle.spill.compress)	Must compress data spilled during shuffles	true, false
Scheduling	LOC_WAIT (locality.wait)	How long to wait to launch a data-local task on a less-local node	10 ms, 100 ms, 500 ms, 1 s, 3 s, 10 s
Serialization	SER (serializer)	Data serialization mechanism	(Java), Kryo
Shuffle	SHF_COMPR (shuffle.compress)	Must compress map output files	true, false
	SFL_BUF (shuffle.file.buffer)	Size of in-memory buffer of shuffle file output stream	8 KB, 32 KB, 64 KB, 128 KB, 256 KB, 512 KB

3 Traces Overview and Analysis

In this section, we first suggest possible uses of the traces collected during our experiments. Then, we present their statistical features.

3.1 Possible Usage of Our Traces

Synthetic Trace Generation. Using our traces' statistical profiles, one can generate synthetic DML traces. Indeed, leveraging trace features such as numbers of tasks, duration and distribution, one can simulate and thus reason about DML systems without the need for real experimentations. We refer to [8, 17, 15] for tools and techniques for synthetic trace generation from real traces.

Workload Modeling and Simulation. Our traces can help modeling DML workloads. Models that capture workload patterns can be used to predict performance. They can also help the optimization of existing DML platforms and even the design of new platforms embedding the workloads' specificities. The analysis and the modeling of workloads has already been considered in different application domains including data centers, the cloud and the web [14, 18, 22].

3.2 Statistical Analysis

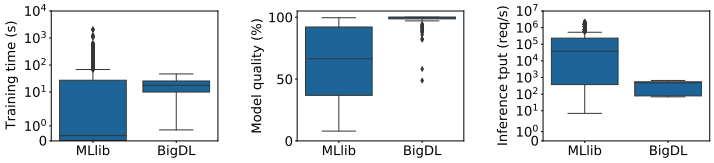
We have harvested metrics at the application-, platform- and the infrastructure levels. Our traces have been collected on both clusters 1 and 2 (see §2.1). They

Table 5. Examples of collected metrics

Application-level metrics	**Description**
Training accuracy	Percentage of predicted values that match the actual values in the training dataset
Inference throughput	Number of records inferred by unit of time
Silhouette	Evaluation metric for clustering methods. It measures how similar an object is to its own cluster
R2 Score	Proportion of the variance in the dependent variable that is predictable from the independent variable(s)
RMSE (root mean square error)	The square root of MSE
F1 score	Harmonic mean between precision and recall
Platform-level metrics	**Description**
Task duration	Total elapsed time
Task deserialization time	Elapsed time spent to deserialize this task
Garbage collection time	Total JVM garbage collection time
Result serialization time	Elapsed time spent serializing the task result
Shuffle wait time	Time that tasks spent blocked waiting for shuffle data to be read from remote machines
Records read	Total number of records read
Infrastructure-level metrics	**Description**
CPU usage	Percentage of used CPU.
Memory usage	Percentage of memory utilization
Network traffic	Amount of bytes read from and written to the network.
Energy consumption	Trapezoidal integral of power measurements collected per second.

Table 6. Collected DML workload traces

Trace description	**#Records**	**#Features**	**Size**
Infrastructure-level traces	43,346,092	11	5.3 GiB
Platform-level traces	41,481,857	42	10.8 GiB
Application-level traces	12,934	18	9.6 MiB
Total	**84,840,883**	**Up to 42**	**16.2 GiB**



(a) Training time (b) Model quality (c) Inference tput.

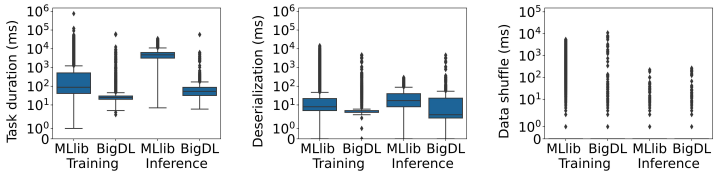
Fig. 1. Distribution of application-level metrics

consist of 16.2 GiB of data with more than 80 millions records (see Table 6). The traces and their detailed description are available on a public archive for the research community [6].

We employ box-and-whiskers plots to report the statistical distribution of our metrics. The values are grouped by the ML library used in the experiments (MLlib or BigDL) and by the learning phase (training or inference).

Application-level Traces. Figure 1 reports the statistical distribution for three of the collected application-level metrics, *i.e.*, training time, accuracy and inference throughput.

Figure 1(a) shows normalized training times for a training set of 1,000 records. In our experiments, MLlib exhibits high variation while BigDL is more stable: 50% of the MLlib cases have very short training times (≤ 0.4 s) and 25%



(a) Task duration (b) Deserialization time (c) Data shuffle

Fig. 2. Distribution of platform-level metrics

have training times between 25 s and 30 min. BigDL training times span between 4 s and 47 s. The greater dataset heterogeneity in our MLlib workloads explains these behaviours if compared to BigDL.

Figure 1(b) gives the models quality metrics: accuracy for classification models, R^2 for regression models and silhouette for clustering models. The median model quality for MLlib workloads is 66.4%, and up to 99.5%. For BigDL, it is between 98% and 100% for 75% of the workloads.

Finally, Figure 1(c) shows that the median inference throughput of our BigDL workloads (476 reqs/s) is less than that of MLlib workloads (around 37,747 requests/s). Infact, classical ML inference is cheaper and more time-efficient than DL-based inference, where the cost is proportional to the network complexity.

Platform-level Traces. Figure 2 represents the distribution of 3 Spark metrics: *(a)* task duration *(b)* task serialization, used upon loading tasks by executors, and *(c)* data shuffling which corresponds to data transfers. Results include both the training and the inference phases.

As shown in Figure 2(a), short tasks (in the 1–100 ms range) are very common with BigDL with up to 79% of the tasks. Less common for MLlib, they are up to 50% for training, and even less for inference where 75% of tasks last at least 3,000 seconds. Longer tasks are more frequent in the inference phase for both MLlib and BigDL. Inference tasks that last more than 100 ms represent 21% for BigDL and up to 98% for MLlib. In training, such tasks represent only 3% for BigDL and 47% for MLlib.

Task deserialization (Figure 2(b)) is very fast (*i.e.*, $\leq$ 10 ms) in 75% of BigDL training tasks, and in 25% to 50% for the other tasks. It is longer (10 ms-10,000 ms) in 75% of MLlib inference tasks but at maximum 50% of the other tasks.

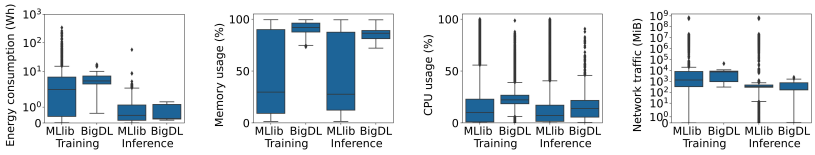
Data shuffling (Figure 2(c)) is negligible for 75% of all tasks. However, it reaches up to 10,000 ms for training tasks and up to 100 ms for inference tasks, *i.e.*, equal to the duration of the whole task (Figure 2(a)).

Infrastructure-level Traces. Figure 3 reports the infrastructure measurements of energy consumption, network traffic, CPU and memory usage. Figure 3(a) indicates that up to 25% of MLlib workloads consume very little energy *i.e.*, $\leq$ than 0.4 Wh. BigDL inference executions consume at least 0.2 Wh and BigDL training at least 0.6 Wh. However, BigDL workloads consume at most

17 Wh whereas the consumption reaches up to 340 Wh for MLlib. This is directly related to the longer MLlib executions.

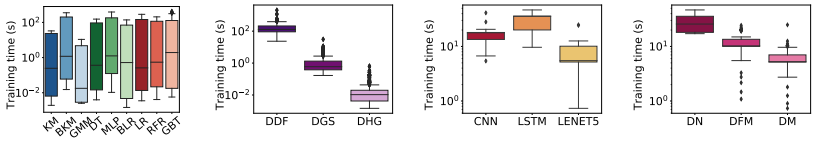
Regarding memory usage, Figure 3(b) shows all our BigDL workloads to be memory-intensive, with at least 70% of memory usage. Also, our workloads are memory-bound and not CPU-bound as CPU usage does not exceed 30% in 75% of all measurements (Figure 3(c)).

Finally, Figure 3(d) shows collected measurements of network traffic. We observe that inference for both MLlib and BigDL workloads involves the lowest network traffic: 75% of inference executions consume at most 800 MiB. In contrast, in 50% of MLlib and BigDL training network traffic exceeds 1 GiB. This is due to the per-iteration exchanges needed to build the model.



(a) Energy consumption (b) Memory usage (c) CPU usage (d) Network traffic

Fig. 3. Distribution of infrastructure-level metrics (CPU usage, memory usage, network usage and energy consumption)



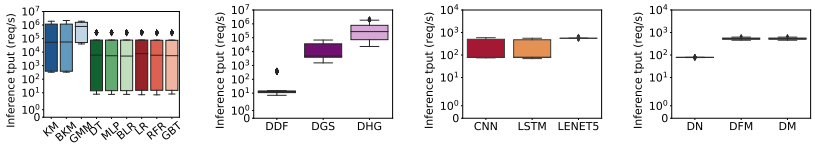
(a) MLlib methods (b) MLlib datasets (c) BigDL methods (d) BigDL datasets

Fig. 4. Training time variability within same DML method (normalized) vs. within same dataset

4 Characterizing DML Workloads

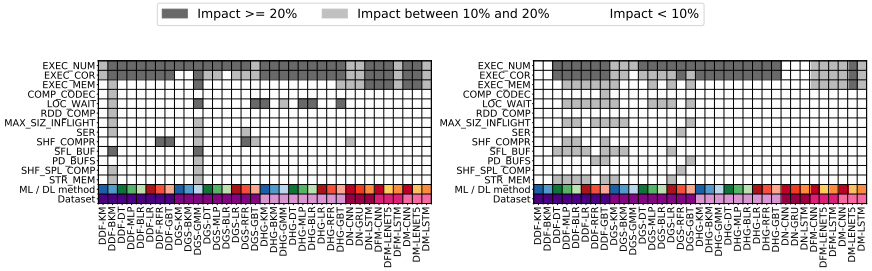
To characterize the sensitivity of DML workloads to different configuration parameters and strategies, we study the effect of varying only platform parameters (§4.1) and of varying only hyper-parameters (§4.2).

These results concern both Cluster 1 and Cluster 2 (see §2.1).



(a) MLlib methods (b) MLlib datasets (c) BigDL methods (d) BigDL datasets

Fig. 5. Inference throughput variability within same DML method vs. within same dataset



(a) Training time (b) Inference throughput

Fig. 6. Impact of platform parameter on performance (dark-grey for high: $> 20\%$, light-grey for medium: $10\% \leq 20\%$, white for low: $< 10\%$). The two bottom rows of each figure refer to the color codes specified in Table 1 and Table 2, respectively.

4.1 Tuning Platform Parameters

We characterize the impact of platform parameters on training time and inference throughput by varying each parameter individually, for each DML workload. We measure the relative variations obtained in performance by each platform parameter. We consider parameters with high impact on performance if their corresponding variation $\geq 20\%$. Parameters which incur variations in the 10%-20% range have medium impact. Finally, if the variations are $\leq 10\%$, we consider those low impact. In the heat map representations of Figures 6(a) and 6(b), we use a 3-color schem (shades of grey), from dark grey (high) to white (low). The considered platform parameters (vertical axis) are presented in §2.3-Table 4).

For the majority of the workloads, the number of Spark executors (`EXEC_NUM`) and the number of cores per executor (`EXEC_COR`) play key roles, as they impact parallelization and performance, particularly while training.

Observation 1 : *DML workloads' performance is significantly impacted by parallelization.*

Figure 6(a) shows that for ensemble learning methods (*e.g.*, random forests and gradient-boosted trees) on datasets with many features (from 100 and beyond) the training phase triggers frequent shuffle operations (`SHF_COMPR` parameter). Examples include `DDF-RFR`, `DDF-GBT`, `DGS-RFR` and `DGS-GBT`, with the

the highest impacts of SHF_COMPR (impact ≥19%) among all workloads. Tuning Spark's shuffle compression parameter, one reduces the amount of data during shuffle, causing less network traffic and therefore faster training time.

Observation 2 : *Training ensemble learning methods on datasets with large number of features significantly benefits from shuffle data size reductions.*

Our large datasets highlight that LOC_WAIT (*i.e.*, the timeout after which a data-local task is launched on a distant node) can significantly affect the training time. Indeed, waiting for an available nearby node for the job would prevent huge data transfers and shuffles that consume time and bandwidth, and thus would significantly impact efficiency. Thus, jobs that deal with large amounts of data benefit from increasing the LOC_WAIT parameter. We observe this phenomenon in particular in Figure 6(a), with the Higgs dataset ((DHG) and four methods for clustering and classification (DHG-KM, DHG-MLP, DHG-BLR and DHG-GBT).

Observation 3 : *Training with large datasets is significantly impacted by task re-scheduling.*

4.2 Tuning Hyper-parameters

We investigate the impact of hyper-parameters on our models' quality, namely accuracy for classification tasks, R^2 coefficient for regression tasks and silhouette score for clustering tasks. We vary individually several hyper-parameters, such as number of iterations, total classes for discretization of continuous variables, the depth of decision tres and others (see the full list in §2.3-Table 3). For each hyper-parameter, we define its impact by the relative performance variations obtained while varying it.

In Figure 7 we distinguish: *(i)* high-impact hyper-parameters for variations beyond 5%, *(ii)* medium-impact for variations in the 5%-1% range, and *(iii)* low-impact parameters, for variations ≤ 1%. Note that empty (*i.e.*, white) cells indicate that the corresponding hyper-parameters have low impact or are irrelevant for the target learning methods. We observe that the *maxIter* hyper-parameter, *i.e.*, the parameter giving the number of iterations for a given learning method, has high impact on the quality of several methods like BKM (Bisecting K-means used in the DDF-BKM, DGS-BKM and DHG-BKM workloads) and MLP (Multi-layer Perception, with DGS-MLP and DHG-MLP workloads). Further, *maxDepth* and *maxBins* are also impactful hyper-parameters for decision-tree (DT) methods.

For BigDL workloads, the number of epochs lightly affect the methods accuracy. Instead, the *stepSize* and *batchSize* hyper-parameters affect several BigDL workloads. Finally, we observe that for many MLlib and BigDL methods (*e.g.*, KM, BKM, GMM, RFR, GBT, DT, LENET5), the learning method is always impacted by the same hyper-parameters, and this holds for any given dataset.

We can thus confirm the general intuition stated below.

Observation 4 : *For many DML workloads, the impact of hyper-parameters on model quality depends more on the type of the learning method than on the nature of data.*

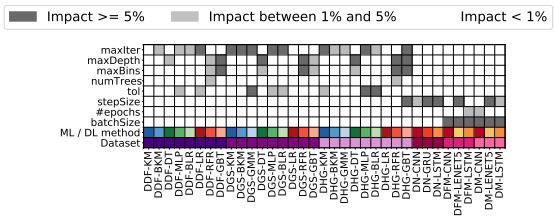


Fig. 7. Impact of hyper-parameter on performance (dark-grey for high: $> 5\%$, light-grey for medium: $1\% \leq 5\%$, white for low: $< 1\%$). The two bottom rows of each figure refer to the color codes specified in Table 1 and Table 2, respectively.

5 Conclusion

We presented our DML workload characterization conducted on diverse and heterogeneous workloads from 13 widely used learning methods, with 6 real-world datasets. We collected extensive execution traces, for a total of 16.2 GiB and over 80 million records. We presented a detailed analysis of the statistical distributions of the collected DML workload traces, showing their main characteristics, and we derived interesting observations to characterize the impact of paltform and hyper-parameters on DML workloads. We publicly release our collected traces [3] to help researchers and practitioners in future DML studies, such as building realistic modeling and simulation tools of DML workloads, or building tools for synthetic DML trace generation.

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