

A Comparison of Support Vector Machines Training GPU-Accelerated Open Source Implementations

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Abstract

Last several years, GPUs are used to accelerate computations in many computer science domains. We focused on GPU accelerated Support Vector Machines (SVM) training with non-linear kernel functions. We had searched for all available GPU accelerated C++ open-source implementations and created an open-source C++ benchmark project. We modified all the implementations to run on actual hardware and software and in both Windows and Linux operating systems. The benchmark project offers making a fair and direct comparison of the individual implementations under the same conditions, datasets, and hardware. In addition, we selected the most popular datasets in the community and tested them. Finally, based on the evaluation, we recommended the best-performing implementations for dense and sparse datasets.

Keywords: Support Vector Machines, SVM, GPU, CUDA, Review, Comparison

1. Introduction

Training an SVM amounts to solving a quadratic programming problem. Very efficient solutions were developed for linear or linearized SVMs. However, nonlinear SVMs solvers are more computationally intensive. Therefore, GPUs computation power has been utilized widely. In Catanzaro et al. (2008) and Carpenter (2009) nice speed-ups on dense data sets were reported with the comparison to LibSVM. However, a significant part of the speed-ups comes from a lack of the LibSVM performance that is not optimized in a high performance manner. A GPU multi-class SVM training was introduced in Herrero-Lopez et al. (2010). In Li et al. (2011), an SVM package under the same name like Catanzaro: GPUSVM was presented. It offers multi-class and cross-validation abilities. The most recent dense GPU implementation is WUSVM published in Tyree et al. (2014). We also found three published implementations for sparse data. The regularized ELLPACK sparse matrix format was used in Lin and Chien (2010). In Cotter et al. (2011), a data clustering was used to improve efficiency by the regularized sparse matrix. In Sopyla et al. (2012) the standard CSR format was used. All the mentioned GPU implementations are developed in nVidia

CUDA. However, also other platforms were in focus: e.g. in Cadambi et al. (2009) FPGA was used, Intel Xeon Phi coprocessor was used in You et al. (2014).

We discussed and compared the above mentioned GPU implementations in detail below. We developed a benchmark framework that ensures a fair comparison of the implementations. The benchmark offers data input/output and time measurement common for all the implementations. Therefore, all the implementations are compared with identical hardware, drivers, compiler, and only the GPU SVM training core varies. The benchmark project is open source and it is available at <https://github.com/OrcusCZ/SVMbenchmark>. The benchmark contains all compared implementations except KMLib, due to it being written in C#. We also compared often out-dated projects on the same data, setup, and actual GPU hardware and results are in Section 3.

2. Included Open Source GPU Implementations

- **LibSVM** published in Fan et al. (2005). The LibSVM is a popular CPU-only implementation that we use as a reference. It is available at <https://www.csie.ntu.edu.tw/~cjlin/libsvm>. The LibSVM stores data in a sparse format. However, the dense variant is available also.
- **GPU-LibSVM** published in Athanasopoulos and Dimou (2011) and available at <http://mklab.iti.gr/project/GPU-LIBSVM>. It is a modification of the dense variant of the LibSVM, where only the computation of the kernel matrix elements in only cross-validation mode is ported to GPU.
- **GPUSVM** published in Catanzaro et al. (2008) and available at <https://code.google.com/p/gpusvm> is a more advanced CUDA implementation of a sequential minimal optimization (SMO).
- **cuSVM** published in Carpenter (2009) available at <http://patternsonascreen.net/cuSVM.html> is practically just a CUDA reimplement of the LibSVM algorithm.
- **MultiSVM** published in Herrero-Lopez et al. (2010) available at <https://code.google.com/p/multisvm> is the first GPU SVM implementation that allows a multi-class classification in the one-vs-all manner besides the two-class problems. A cross-task kernel caching technique is used to significantly reduce total amount of computations needed.
- **gtSVM** published in Cotter et al. (2011) available at <http://ttic.uchicago.edu/~cotter/projects/gtsvm> uses sparse data format. It does not use SMO but it uses a larger working set of size 16. A clustering algorithm is used to regularize sparsity patterns in data and permits better memory access. The size of the clusters can be selected from two options: large or small that means 256 or 16 samples, respectively. In the results Section 3 we marked the large clusters and the small clusters variants as "gtSVM LC" and "gtSVM SC", respectively.
- **WUSVM** published in Tyree et al. (2014) is available at <https://github.com/wusvm>. A sparse primal SVM variant of the training algorithm is implemented in

WUSVM. However the algorithm contains random shuffling of the training data by default that brings a stochastic component that produces models with variable performance in variable training times.

- **KMLib** published in Sopyla and Drozda (2015) is written in C# and uses CUDA.NET library. The library supports several SVM kernels and also several sparse data formats, most notably Sliced EllR-T format introduced by this library.

3. Results

We tried to test all the implementations on the same datasets that were frequently used in the referenced publications. We used both dense and sparse datasets and converted some small sparse datasets to dense form. We performed the two-class SVM training with RBF kernel function because it is supported by all the tested implementations. A complete list of used datasets and the training setup is in Table 1. *Epsilon* and *Alpha* datasets come from the Pascal Large Scale Learning Challenge <http://largescale.ml.tu-berlin.de>. They are very large dense datasets and most implementations cannot handle them so we used only subsets of them. Scaling is used for *Epsilon* and *Alpha* datasets. The rest of the datasets come from the LibSVM data page: <https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/>. *Timit* and *MNIST* are multi-class tasks, we converted them to binary task by classifying even-vs-odd class index. *Adult* and *Web* sets are the most popular SVM datasets and we used the biggest variants of the sets: *Adult a9a* and *Web w8a*. *Cov1 Forest* is a set of cartographic variables for detection of the cover type. It is multi-class task but we used it as a detection of cover type 1 that is forest. *20 Newsgroups*, *RCV1*, and *Real-Sim* are large sparse sets for the text categorization and the training data were used also as a testing ones for these three sets. We used a desktop PC with Intel Core i7-4790K, 4-core CPU clocked at 4.0GHz, 32 GB RAM and Pascal-based NVIDIA GTX 1080 with 2560 cores clocked at 1607 MHz and 8 GB GDDR5 with bandwidth 320 GB/s.

Dense datasets match better to the GPU architecture and speed-up over LibSVM may be very high because LibSVM processes data in sparse format. The results are in table 2. The best results are bold. The reference LibSVM and LibSVM-dense implementations were set to use the maximum cache size equal to size of the GPU memory, so 8 GB was set in table 2. The fastest implementation is the GPUSVM for *Epsilon 40k* and *Alpha 10k* and gtSVM for other datasets except *Cov1 Forest*. cuSVM was able to outperform other implementations on *Cov0 Forest* dataset. MultiSVM and gtSVM trained bad model with very low accuracy for *Cov1 Forest*. wuSVM is inconsistent and each training takes different time. The table contains training time average observed in 10 tests. All other trained models gave the same accuracy on test sets as the LibSVM reference. Sparse datasets are harder to handle on GPUs. However, very high speed-ups were achieved for sparse sets also. The results are in table 3. The gtSVM implementation has two variants: the large clusters and the small clusters marked as "gtSVM LC" and "gtSVM SC", respectively. The large clusters variant gave better elapsed times for small sets with medium sparsity while the small cluster variant excelled on large and very sparse datasets. However, the *Cov1 Forest* model gave very low accuracy. KMLib's training times were worse than gtSVM for all datasets except *20 Newsgroups* and *RCV1*, but it was able to train good model for *Cov1 Forest*. The

medium sparse datasets can be trained in the dense form also, however, the dense GPUSVM achieved slightly worse training times than the sparse gtSVM.

Table 1: List of used datasets with the main features and the training setup.

Dataset	# Training Samples	# Test Samples	# Dimensions	Dense / Sparse	C	Gamma
Epsilon 40k	40,000	10,000	2,000	Dense	32	0.0001
Alpha 10k	10,000	50,000	500	Dense	512	0.002
Timit	63,881	22,257	39	Dense	1	0.025
Adult a9a	32,561	16,281	123	Sparse	4	0.5
Web w8a	49,749	14,951	300	Sparse	4	0.5
MNIST	60,000	10,000	784	Sparse	1	0.02
Cov1 Forest	522,911	58,101	54	Sparse	3	1.0
20 Newsgroups	19,996	19,996	1,335,191	Sparse	4	0.5
RCV1	20,242	677,399	47,236	Sparse	4	0.5
Real-Sim	72,309	72,309	20,958	Sparse	4	0.5

Table 2: Elapsed time of the SVM training in seconds on Pascal-based NVIDIA 1080 GPU and the dense datasets. WM means ”wrong model”

Dataset	Epsilon 40k	Alpha 10k	Timit	Adult a9a	Web w8a	MNIST	Cov1 Forest
LibSVM	1,526	57.5	159.1	69.3	237.2	275.6	6,990
LibSVM-dense	1,091	46.8	151.1	136.7	815.6	289.4	14,004
cuSVM	39.25	101.38	17.04	17.45	22.02	11.92	265.27
gpuSVM	28.04	26.26	2.86	3.36	7.58	5.89	301.04
multiSVM	51.34	90.04	17.73	18.69	22.52	12.22	WM ¹ (191.05)
wuSVM	122.08	61.96	203.86	131.56	13.61	79.21	596.86
gtSVM LC	47.80	31.45	2.43	3.19	4.02	3.72	WM ¹ (61.25)
gtSVM SC	77.22	36.38	3.17	3.37	4.43	4.55	WM ¹ (112.12)

Table 3: Elapsed time of the SVM training in seconds on Pascal-based NVIDIA 1080 GPU and the sparse datasets. WM means ”wrong model”

Dataset	Adult a9a	Web w8a	MNIST	Cov1 Forest	20 Newsgroups	RCV1	Real-Sim
LibSVM	69.3	237.2	275.6	6,990	604.3	63.2	564.4
gtSVM LC	3.30	4.03	3.69	WM ¹ (61.17)	605.53	15.83	53.66
gtSVM SC	3.44	4.27	4.60	WM ¹ (111.58)	486.83	10.11	20.81
KMLib	18.65	19.30	21.55	874.65	145.01	10.02	55.80

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