SOL: A library for scalable online learning algorithms

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SOL: A library for scalable online learning algorithms

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A B S T R A C T

SOL is an open-source library for scalable online learning with high-dimensional data. The library provides a family of regular and sparse online learning algorithms for large-scale classification tasks with high efficiency, scalability, portability, and extensibility. We provide easy-to-use command-line tools, python wrappers and library calls for users and developers, and comprehensive documents for both beginners and advanced users. SOL is not only a machine learning toolbox, but also a comprehensive experimental platform for online learning research. Experiments demonstrate that SOL is highly efficient and scalable for large-scale learning with high-dimensional data.

Software metadata

(executable) Software metadata description

Current software version: v1.1.0
Permanent link to executables of this version: https://github.com/Neurocomputing/NEUCOM-D-16-02987
Legal Software License: Apache 2.0 open source license
Computing platform / Operating system: Linux, OS X, Windows.
Installation requirements & dependencies: C++11 Compiler, (Python 2.7)
Link to user manual: https://github.com/libol/sol/wiki
Support email for questions: chhoi@smu.edu.sg

Code metadata

Code metadata description

Current code version: v1.1.0
Permanent link to code/repository used of this code version: https://github.com/Neurocomputing/NEUCOM-D-16-02987
Legal Code License: Apache 2.0 open source license
codeversioning system used: git
Software code languages, tools, and services used: C++/Python
Compilation requirements, operating environments & dependencies: GCC/MSVC/Clang, Python2.7
If available Link to developer documentation/manual: https://github.com/libol/sol/wiki
Support email for questions: chhoi@smu.edu.sg
1. Introduction

In the era of big data, data is large not only in sample size, but also in feature/dimension size, e.g., web-scale text classification with millions of dimensions. Traditional batch learning algorithms fall short in low efficiency and poor scalability, e.g., high memory consumption and expensive cost for re-training new data. Online learning represents a family of efficient and scalable algorithms that sequentially learn one example at a time. Some existing toolboxes, e.g., LIBOL [1], allows researchers in academia to benchmark different online learning algorithms, but it was not designed for practical developers to tackle online learning with large-scale high-dimensional data in industry.

In this work, we develop SOL as an easy-to-use scalable online learning toolbox for large-scale binary and multi-class classification tasks. It includes a family of ordinary and sparse online learning algorithms, and is highly efficient and scalable for processing high-dimensional data by using (i) parallel threads for both loading and learning the data, and (ii) specially designed data structure for high-dimensional data. The library is implemented in standard C++ with the cross platform ability and there is no dependency on other libraries. To facilitate developing new algorithms, the library is carefully designed and documented with high extensibility. We also provide python wrappers to facilitate experiments and library calls for advanced users. The SOL website is host at http://sol.stevenhoi.org and the software is made available https://github.com/libol/sol.

2. Scalable online learning for large-scale linear classification

2.1. Overview

Online learning operates sequentially to process one example at a time. Consider \( \{ (x_t, y_t) | t \in [1, T] \} \) be a sequence of training data examples, where \( x_t \in \mathbb{R}^d \) is a \( d \)-dimensional vector, \( y_t \in \{+1, -1\} \) for binary classification or \( y_t \in \{0, \ldots, C-1\} \) for multi-class classification \( \mathcal{C} \). As Algorithm 1 shows, at each step \( t \), the learner receives an incoming example \( x_t \) and then predicts the scores \( y_t \) over classes. Afterward, the true label \( y_t \) is revealed and the learner suffers a loss \( \ell(y_t, \hat{y}_t) \), e.g., the hinge loss is commonly used \( \ell(y_t, \hat{y}_t) = \max(0, 1 - y_t \cdot \hat{y}_t) \) for binary classification. For sparse online learning one, can modify the loss with L1 regularization \( \ell(y_t, \hat{y}_t) + \lambda \| w \|_1 \) to induce sparsity for the learned model \( w \). At the end of each learning step, the learner decides when and how to update the model.

Algorithm 1: SOL: Online Learning Framework for Linear Classification.

```
Initialize: \( w_0 = 0 \).
for \( t = 1: T \) do
    Receive \( x_t \in \mathbb{R}^d \), predict \( \hat{y}_t \), receive true label \( y_t \);
    Suffer loss \( \ell(y_t, \hat{y}_t) \);
    if \( \ell(y_t, \hat{y}_t) \) then
        \[ w_{t+1} = update(w_t) \]
    end
end
```

The goal of our work is to implement most state-of-the-art online learning algorithms to facilitate research and application purposes on the real world large-scale high dimensional data. Especially, we include sparse online learning algorithms which can effectively learn important features from the high dimensional real world data [2]. We provide algorithms for both binary and multi-class problems. These algorithms can also be classified into first order algorithms [3] and second order algorithms [4] from the model’s perspective. The implemented algorithms are listed in Table 1.

| Type              | Methodology | Algorithm      | Description                        |
|-------------------|-------------|----------------|------------------------------------|
| Online            | First order | Perceptron     | The perceptron algorithm            |
| learning          |             | OGD            | Online gradient descent            |
|                   |             | PA             | Passive aggressive algorithms       |
|                   |             | ALMA           | Approximate large margin algorithm  |
|                   |             | RDA            | Regularized dual averaging          |
|                   |             | SOP            | Second-order perceptron             |
|                   |             | CW             | Confidence weighted learning        |
|                   |             | ECCW           | Exactly convex confidence weighted learning |
|                   | Second order| AROW           | Adaptive regularized online learning |
|                   |             | Ada-FOBOS-L1   | Adaptive gradient descent           |
|                   |             | Ada-RDA-L1     | Adaptive dualized regularization    |
| Sparse            | First order | STG            | Sparse online learning via          |
| online            |             | FOBOS-L1       | truncated gradient                  |
| learning          |             | RDA-L1         | Mixed \( l_1/\ell_2 \) regularized dual averaging |
|                   |             | ERDA-L1        | Enhanced \( l_1/\ell_2 \) regularized dual averaging |
|                   | Second order| Ada-FOBOS-L1   | Ada-FOBOS with \( l_1 \) regularization |
|                   |             | Ada-RDA-L1     | Ada-RDA with \( l_1 \) regularization |

2.2. The software package

The SOL package includes a library, command-line tools, and python wrappers for the learning task. SOL is implemented in standard C++ to be easily compiled and built in multiple platforms (Linux, Windows, MacOS, etc.) without dependency. It supports “libsvm” and “csv” data formats. To accelerate the training process, a binary format is defined. SOL is released under the Apache 2.0 open source license.

2.2.1. Practical usage

To illustrate the training and testing procedure, we use the OGD algorithm with a constant learning rate 1 to learn a model for the “rcv1\textsuperscript{1}” dataset and save the model to “rcv1.model”.

```bash
$ sol_train --params eta=1 -a ogd rcv1_train rcv1.model
(output skipped)
$ sol_test rcv1.model rcv1_test predict.txt
```

We can also use the python wrappers to train the same model. The wrappers provide the cross validation ability which can be used to select the best parameters as the following commands show. More advanced usages of SOL can be found in the documentation.

```bash
$ sol2_train.py --cv cv=0.25-2.128 -a ogd rcv1_train rcv1.model
cross validation parameters: [‘[eta’, 32.0]]
$ sol2_test.py rcv1.model rcv1_test predict.txt
test accuracy: 0.9744
```

2.2.2. Documentation and design

The SOL package comes with detailed documentation. The README file gives an “Installation” section for different platforms.

\[1\] https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/binary.html#rcv1.binary
and a “Quick Start” section as a basic tutorial to use the package for training and testing. We also provide online Wiki for advanced users. Users who want to have a comprehensive evaluation of online algorithms and parameter settings can refer to the “Command” section. If users want to call the library in their own project, they can refer to the “Library” section. For those who want to implement a new algorithm, they can read the “Design” section and the “Extension Examples” section. The whole package is designed for high efficiency, scalability, portability, and extensibility.

- Efficiency: it is implemented in C++ and optimized to reduce time and memory cost.
- Scalability: Data samples are stored in a sparse structure. All operations are optimized around the sparse data structure.
- Portability: All the codes follow the C++11 standard, and there is no dependency on external libraries. We use “cmake” to organize the project so that users on different platforms can build the library easily. SOL thus can run on almost every platform.
- Extensibility: (i) the library is written in a modular way, including PARIO(for PARallel IO), Loss, and Model. User can extend it by inheriting the base classes of these modules and implementing the corresponding interfaces; (ii) We try to relieve the pain of coding in C++ so that users can implement algorithms in a “Matlab” style. The code snippet in Fig. 1 shows an example to implement the core function of the “ALMA” algorithm.

2.3. Comparisons

Due to space limitation, we only demonstrate that: (1) the online learning algorithms quickly reach comparable test accuracy compared to L2-SVM in LIBLINEAR [14] and VW; (2) the sparse online learning methods can select meaningful features compared to L1-SVM in LIBLINEAR and L1-SCD in VW. According to Table 2, SOL provides a wide variety of algorithms that can achieve comparable test accuracies as LIBLINEAR and VW, while the training time is significantly less than LIBLINEAR. VW is also an efficient and effective online learning tool, but may not be a comprehensive platform for researchers due to its limited number of algorithms and somewhat complicated design. Fig. 2 shows how the test accuracy varies with model sparsity. L1-SVM does not work well in low sparsity due to inappropriate regularization. According to the curves, the Ada-RDA-L1 algorithm achieves the best test accuracy for almost all model sparsity values. Clearly, SOL is a highly efficient and effective online learning toolbox. More empirical results on other datasets can be found at https://github.com/libol/sol/wiki/Example.


Table 2

| Algorithm | Train time(s)  | Accuracy | Algorithm | Train time(s)  | Accuracy |
|-----------|---------------|----------|-----------|---------------|----------|
| Perceptron | 8.4296 ± 0.0867 | 0.9625 ± 0.0014 | OGD       | 8.4109 ± 0.0982 | 0.9727 ± 0.0006 |
| PA        | 8.4506 ± 0.1031 | 0.9649 ± 0.0015 | PA1       | 8.5113 ± 0.0143 | 0.9760 ± 0.0005 |
| PA2       | 8.4445 ± 0.1068 | 0.9758 ± 0.0003 | ALMA      | 9.1464 ± 0.1624 | 0.9745 ± 0.0009 |
| RDA       | 8.4809 ± 0.0899 | 0.9212 ± 0.0000 | ERDA      | 8.4623 ± 0.1123 | 0.9403 ± 0.0002 |
| CW        | 8.4356 ± 0.1118 | 0.9565 ± 0.0010 | ECCV      | 8.4641 ± 0.1116 | 0.9681 ± 0.0009 |
| SOP       | 8.5246 ± 0.1037 | 0.9627 ± 0.0012 | AROW      | 8.4390 ± 0.1292 | 0.9766 ± 0.0002 |
| Ada-FOROS | 8.4897 ± 0.0872 | 0.9796 ± 0.0003 | Ada-RDA  | 8.4388 ± 0.1140 | 0.9767 ± 0.0003 |
| VW        | 11.3581 ± 0.3423 | 0.9754 ± 0.0009 | LIBLINEAR | 77.9274 ± 1.4742 | 0.9771 ± 0.0000 |

Fig. 1. Example code to implement the core function of “ALMA” algorithm.

Fig. 2. Comparison of sparse online learning algorithms.

2.4. Illustrative examples

Illustrative examples of SOL can be found at: https://github.com/libol/sol/wiki/Example.

3. Conclusion

SOL is an easy-to-use open-source package of scalable online learning algorithms for large-scale online classification tasks. SOL enjoys high efficiency and scalability in practice, particularly when dealing with high-dimensional data. In the era of big data, SOL is not only a sharp knife for machine learning practitioners in learning with massive high-dimensional data, but also a comprehensive research platform for online learning researchers.

Required metadata

Current executable software version

Ancillary data table required for sub version of the executable software: (x.1, x.2 etc.) kindly replace examples in right column with the correct information about your executables, and leave the left column as it is.

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2 https://github.com/JohnLangford/vowpal_wabbit. VW is another OL tool with only a few algorithms.
Current code version

Ancillary data table required for subversion of the codebase. Kindly replace examples in right column with the correct information about your current code, and leave the left column as it is.

Acknowledgments

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References

[1] S.C. Hoi, J. Wang, P. Zhao, Libol: a library for online learning algorithms, J. Mach. Learn. Res. 15 (1) (2014) 495–499.
[2] J. Langford, L. Li, T. Zhang, Sparse online learning via truncated gradient, J. Mach. Learn. Res. 10 (2009) 777–801.
[3] L. Xiao, Dual averaging methods for regularized stochastic learning and online optimization, J. Mach. Learn. Res. 9999 (2010) 2543–2596.
[4] K. Crammer, A. Kulesza, M. Dredze, Adaptive regularization of weight vectors, Mach. Learn. (2009) 1–33.
[5] F. Rosenblatt, The perceptron: a probabilistic model for information storage and organization in the brain., Psychol. Rev. 65 (6) (1958) 386.
[6] M. Zinkevich, Online convex programming and generalized infinitesimal gradient ascent (2003), in: Ref. [6].
[7] K. Crammer, O. Dekel, J. Keshet, S. Shalev-Shwartz, Y. Singer, Online passive-aggressive algorithms, J. Mach. Learn. Res. 7 (2006) 551–585.
[8] C. Gentile, A new approximate maximal margin classification algorithm, J. Mach. Learn. Res. 2 (2002) 213–242.
[9] N. Cesa-Bianchi, A. Conconi, C. Gentile, A second-order perceptron algorithm, SIAM J. Comput. 34 (3) (2005) 640–668.
[10] M. Dredze, K. Crammer, F. Pereira, Confidence-weighted linear classification, in: Proceedings of the 25th international conference on Machine learning, ACM, 2008, pp. 264–271.
[11] K. Crammer, M. Dredze, F. Pereira, Exact convex confidence-weighted learning, in: Proceedings of the Advances in Neural Information Processing Systems, 2008, pp. 345–352.
[12] J. Duchi, E. Hazan, Y. Singer, Adaptive subgradient methods for online learning and stochastic optimization, J. Mach. Learn. Res. 12 (2011) 2121–2159.
[13] J. Duchi, Y. Singer, Efficient online and batch learning using forward backward splitting, J. Mach. Learn. Res. 10 (2009) 2899–2934.
[14] R.-E. Fan, K.-W. Chang, C.-J. Hsieh, X.-R. Wang, C.-J. Lin, Liblinear: a library for large linear classification, J. Mach. Learn. Res. 9 (2008) 1871–1874.

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Doyen SAHOO is a Ph.D. Candidate in School of Information Systems, Singapore Management University. He is supervised by Associate Professor Steven C.H. HOI. His primary research topic is Online Learning with nonlinear models. He works on theoretical aspects of machine learning with focus on Online Learning, Deep Learning and Multiple Kernel Learning. He also works on applications of machine learning to Portfolio Optimization and Cyber-Security. Prior to starting PhD, Doyen completed his B.Eng. in Computer Science from Nanyang Technological University.

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