WAKE FOREST UNIVERSITY

Department of Computer Science

S-Step Dual Coordinate Descent for Dual Support Vector Machines

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Introduction

Support Vector Machine (SVM) (Boser et al., 1992) are supervised learning models used for classification tasks by finding the hyperplane (or set of hyperplanes) in a high-dimensional space. The primal problem could be reconstructed by introducing two lagrangian multipliers: α, μ. Therefore, the SVM problem could be reformed to:

L1-SVM with kernel

$$\mathcal{L} = \arg\min_{\alpha} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\alpha_i\alpha_j y_i y_j \mathcal{K}(a_{i,:}a_{j,:}^T) - \sum_{i=1}^{m}\alpha_i \quad (1)$$

L2-SVM with kernel

$$\mathcal{L} = \arg\min_{\alpha} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\alpha_i\alpha_j y_i y_j \mathcal{K}(a_{i,:}a_{j,:}^T) - \sum_{i=1}^{m}\alpha_i + \frac{1}{4C}\sum_{i=1}^{n}{\alpha_i}^2 \quad (2)$$

Preliminary results indicate substantial improvements in running time without sacrificing the quality of solution, thereby making s-step DCD a promising method for large-scale sparse machine-learning tasks.

Methodology

Considering the matrix $A \in \mathcal{R}^{m*n}$

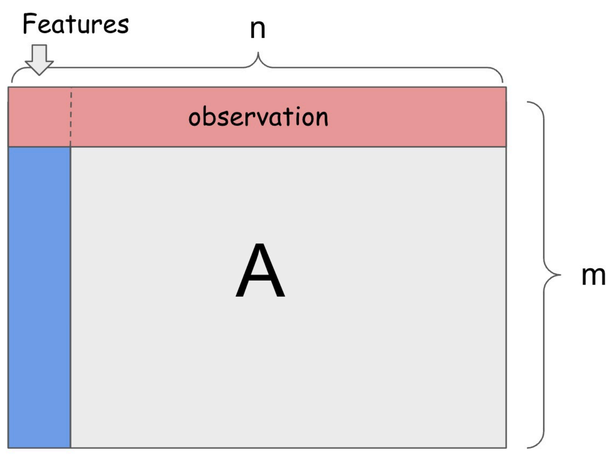


Figure 1: Definition of Trainset Matrix A

We adapt the dual coordinate descent algorithm in parallel computation with OpenMPI in C program. The matrix was partitioned with features, which allows the program to perform local computations of kernel and communicate until all local computation are finished.

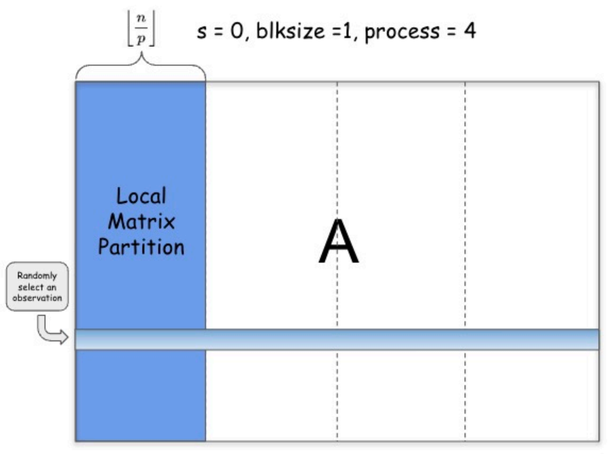


Figure 2: Partition the dataset by features

The gram matrix was then computed by AA^T

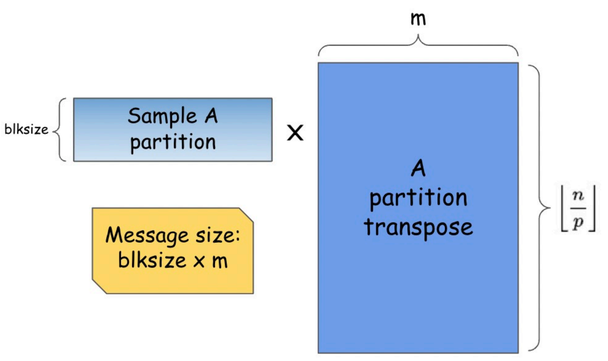


Figure 3: Gram Matrix Computation, DCD

S-step method works by selecting s block of observations with replacement, conduct local gram matrix computations and communicate s times more information, thereby reduce the latency time with a sacrifice in bandwidth cost.

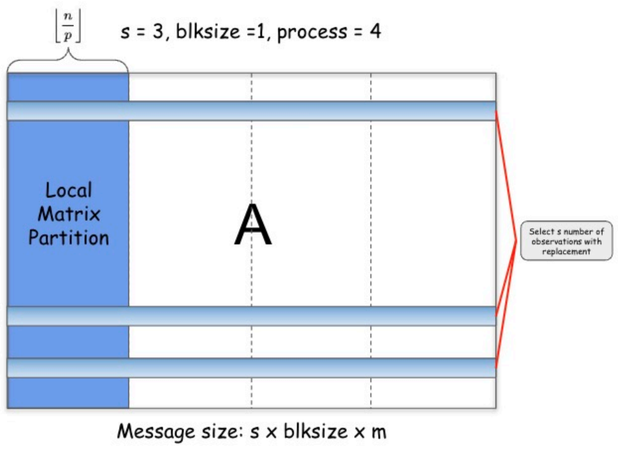


Figure 4: Partition the dataset by features

The gram matrix of s-step method was computed by:

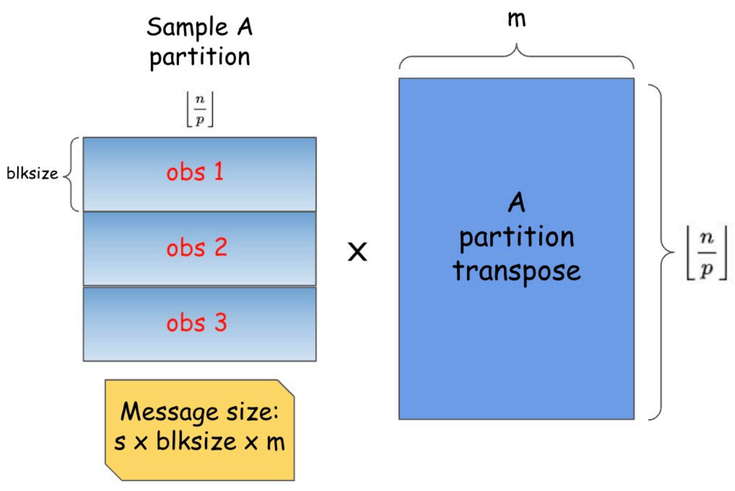


Figure 5: Gram Matrix Computation, DCD

Result

Convergence Experiment:

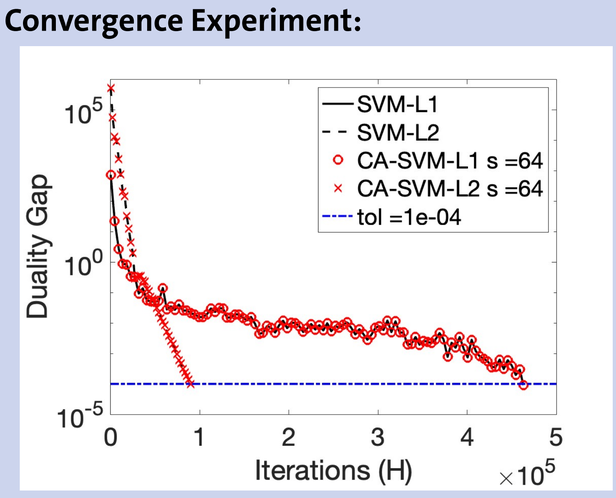
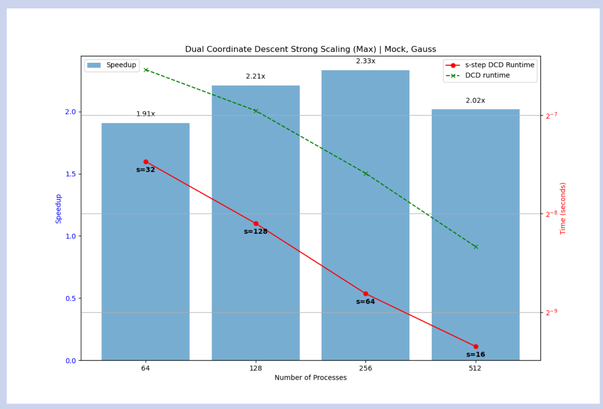


Figure 6: Convergence behavior, DCD, diabete

Strong scaling Experiment:



Runtime Breakdown:

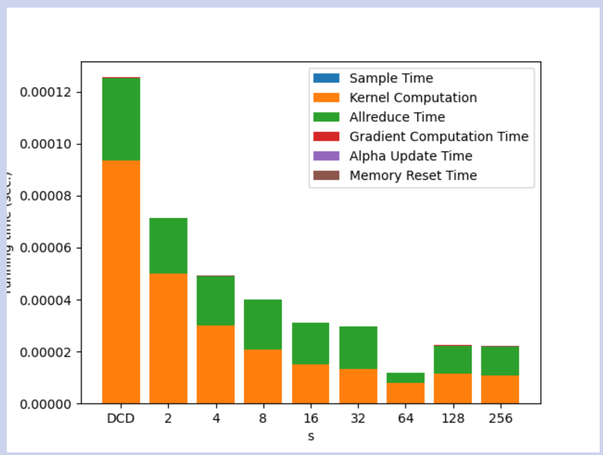


Figure 7: Duke Breast-Cancer, gauss

References

[1] Bernhard E. Boser, Isabelle M. Guyon, and Vladimir N. Vapnik. A training algorithm for optimal margin classifiers. In *Proceedings of the Fifth Annual Workshop on Computational Learning Theory*, COLT '92, page 144–152, New York, NY, USA, 1992. Association for Computing Machinery.

[2] Aditya Devarakonda. Avoiding communication in first order methods for optimization. 2018.

[3] Cho-Jui Hsieh et al. A dual coordinate descent method for large-scale linear svm. In *Proceedings of the 25th International Conference on Machine Learning - ICML '08*, 2008.