

GPU Accelerated Support Vector Machines via Quadratic Programming

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Objective

Solve classification problems quickly

- Support Vector Machines
- ADMM Algorithm
- CPU and GPU Implementations
- Results

Paper from Oxford Control Group (part of osqp)

GPU Acceleration of ADMM for Large-Scale Quadratic Programming [2]

Michel Schubiger, Goran Banjac, and John Lygeros - 2019

Support Vector Machine

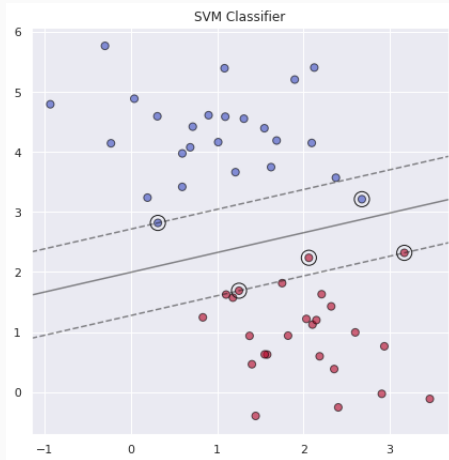


Figure 1: Cartoon of an SVM classification problem

We can write the SVM problem as one that relies on convex optimization, specifically *quadratic programming*

$$\{x : f(x) = x^T \beta + 1 = 0\} \quad (1)$$

Support Vector Machine

We can write the SVM problem as one that relies on convex optimization, specifically *quadratic programming* [1]

$$L_P = \frac{1}{2} \|\beta\|^2 + C \sum_{i=1}^N \xi_i - \sum_{i=1}^N \alpha_i [y_i (x_i^T \beta + 1) - (1 - \xi_i)] - \sum_{i=1}^N \mu_i \xi_i \quad (2)$$

$$L_D = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j x_i^T x_j \quad (3)$$

$$\alpha_i [y_i (x_i^T \beta + 1) - (1 - \xi_i)] = 0 \quad (4)$$

$$\mu_i \xi_i = 0 \quad (5)$$

$$y_i (x_i^T \beta + 1) - (1 - \xi_i) \geq 0 \quad (6)$$

This allows us to solve the SVM problem with an algorithm called ADMM

Alternating Direction Method of Multipliers

- A technique to minimize convex functions
- Intuition: Try to minimize a convex function by alternatively minimize Lagrangian in different directions

Algorithm 1: ADMM algorithm as presented in [3]

given: x^0, z^0, y^0 and parameters $\rho > 0, \sigma > 0, \alpha \in [0, 2]$

while *not terminated* **do**

$$(\tilde{x}^{k+1}, v^{k+1}) \leftarrow \begin{bmatrix} P + \sigma I & A^T \\ A & -\rho^{-1}I \end{bmatrix} \begin{bmatrix} \tilde{x}^{k+1} \\ v^{k+1} \end{bmatrix} = \begin{bmatrix} \sigma x^k - q \\ z^k - \rho^{-1}y^k \end{bmatrix}$$

$$\tilde{z}^{k+1} \leftarrow z^k + \rho^{-1}(v^{k+1} - y^k)$$

$$x^{k+1} \leftarrow \alpha \tilde{x}^{k+1} + (1 - \alpha)x^k$$

$$z^{k+1} \leftarrow \alpha \tilde{z}^{k+1} + (1 - \alpha)z^k + \rho^{-1}y^k$$

$$y^{k+1} \leftarrow y^k + \rho(\alpha \tilde{z}^{k+1} + (1 - \alpha)z^k - z^{k+1})$$

end

Issue: solving this linear system is challenging

$$\begin{bmatrix} P + \sigma I & A^T \\ A & -\rho^{-1}I \end{bmatrix} \begin{bmatrix} \tilde{x}^{k+1} \\ v^{k+1} \end{bmatrix} = \begin{bmatrix} \sigma x^k - q \\ z^k - \rho^{-1}y^k \end{bmatrix} \quad (7)$$

Issue: solving this linear system is challenging

$$\begin{bmatrix} P + \sigma I & A^T \\ A & -\rho^{-1}I \end{bmatrix} \begin{bmatrix} \tilde{x}^{k+1} \\ v^{k+1} \end{bmatrix} = \begin{bmatrix} \sigma x^k - q \\ z^k - \rho^{-1}y^k \end{bmatrix} \quad (8)$$

- Use LDL Factorization
- Use Preconditioned Conjugate Gradient (PCG)

Algorithm 2: PCG algorithm as presented in [2]

initialise: $r^0 = Kx^0 - b$, $y^0 = M^{-1}r^0$, $p^0 = -y^0$, $k = 0$

while $\|r^k\| > \epsilon\|b\|$ **do**

$$\alpha^k \leftarrow -\frac{(r^k)^T y^k}{(p^k)^T K p^k}$$

$$x^{k+1} \leftarrow x^k + \alpha^k p^k$$

$$r^{k+1} \leftarrow r^k + \alpha^k K p^k$$

$$y^{k+1} \leftarrow M^{-1} r^{k+1}$$

$$\beta^{k+1} \leftarrow -\frac{(r^{k+1})^T y^{k+1}}{(r^k)^T y^k}$$

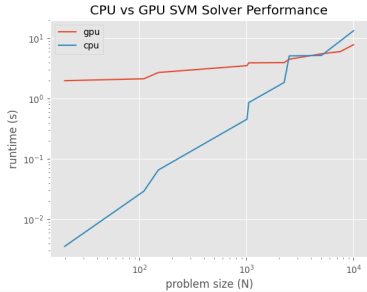
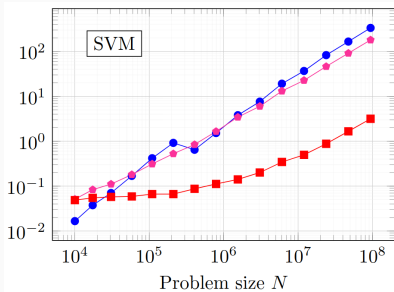
$$p^{k+1} \leftarrow -y^{k+1} + \beta^{k+1} p^k$$

$$k \leftarrow k + 1$$

end

- matrix representation - CSR
- cuBLAS
- cuSPARSE

Results





T. Hastie, R. Tibshirani, and J. Friedman.

The Elements of Statistical Learning.

Springer Series in Statistics. Springer New York Inc., New York, NY, USA, 2001.



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arXiv:1912.04263, 2019.



B. Stellato, G. Banjac, P. Goulart, A. Bemporad, and S. Boyd.

OSQP: An operator splitting solver for quadratic programs.

Mathematical Programming Computation, 2020.