

A few slides on Interior Point SVM entries

For PASCAL Largescale Learning Challenge workshop

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4th July 2008

Linear SVM using interior point method

Primal formulation

$$\begin{aligned} \min_{\underline{w}, w_0, \underline{\xi}} \quad & \frac{1}{2} \underline{w}^T \underline{w} + C \underline{e}^T \underline{\xi} \\ \text{s.t.} \quad & Y(X^T \underline{w} + w_0 \underline{e}) \geq \underline{e} - \underline{\xi} \\ & \underline{\xi} \geq \underline{0} \end{aligned}$$

Very many constraints $\Rightarrow \mathcal{O}(n^2)$

Dual formulation

$$\begin{aligned} \min_{\underline{\alpha}} \quad & \frac{1}{2} \underline{\alpha}^T YX^T XY \underline{\alpha} - \underline{e}^T \underline{\alpha} \\ \text{s.t.} \quad & \underline{y}^T \underline{\alpha} = 0 \\ & \underline{0} \leq \underline{\alpha} \leq C \underline{e} \end{aligned}$$

Dense Hessian $\Rightarrow \mathcal{O}(n^3)$

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Dense Hessian $\Rightarrow \mathcal{O}(n^3)$

Separable formulation

$$\begin{aligned} \min_{\underline{w}, \underline{\alpha}} \quad & \frac{1}{2} \underline{w}^T \underline{w} - \underline{e}^T \underline{\alpha} \\ \text{s.t.} \quad & \underline{w} - XY \underline{\alpha} = \underline{0} \\ & \underline{y}^T \underline{\alpha} = 0 \\ & \underline{0} \leq \underline{\alpha} \leq C \underline{e}. \end{aligned}$$

Based on dual formulation.

Few constraints $\Rightarrow \mathcal{O}(m^2)$

Diagonal Hessian $\Rightarrow \mathcal{O}(n)$

Direct access to \underline{w} and w_0 using primal-dual IPM

Efficient computations on multi-core processors

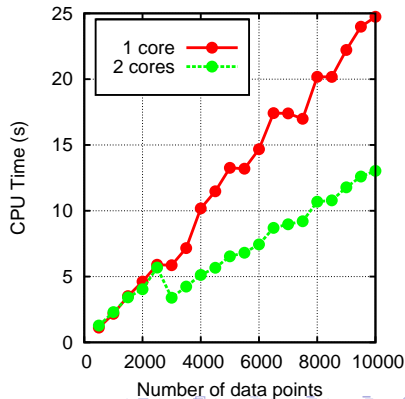
Vast majority of time ($> 95\%$) is spent calculating matrix M :

$$M \equiv \begin{bmatrix} I_m & -XY \\ 0 & \underline{y}^T \end{bmatrix} \begin{bmatrix} I_m & 0 \\ 0 & \Theta_\alpha^{-1} \end{bmatrix}^{-1} \begin{bmatrix} I_m & 0 \\ -YX^T & \underline{y} \end{bmatrix}$$

Θ_α is diagonal matrix associated with logarithmic barrier.

Aim to minimize number of layer 2 cache misses:

- Divide data into “cache-sized” blocks
- Use BLAS Level 3 operations as much as possible (here DGEMM)
- BLAS libraries support **shared memory threading** across processor cores e.g. GotoBLAS, Intel MKL
- Layer 2 cache misses $\approx 2\%$ of data reads



Termination based on hyperplane stability

- w (hyperplane) converges remarkably quickly
- α , duality gap and residual errors converge afterwards
- Use hyperplane stability for termination in version 2

Angle ϕ of hyperplane between iteration $i - 1$ and i

$$\cos \phi = \frac{(w^{(i-1)})^T w^{(i)}}{\|w^{(i-1)}\| \|w^{(i)}\|}$$

Precision recall and change in hyperplane angle for alpha dataset:

