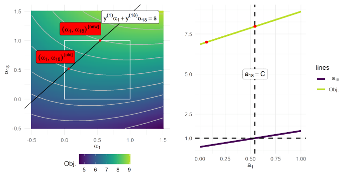
Introduction to Machine Learning

Linear Support Vector Machines
Support Vector Machine Training



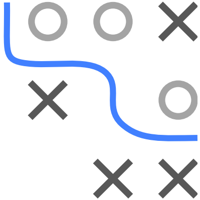
Learning goals

- Know that the SVM problem is not differentiable
- Know how to optimize the SVM problem in the primal via subgradient descent
- Know how to optimize SVM in the dual formulation via pairwise coordinate ascent

SUPPORT VECTOR MACHINE TRAINING

- Until now, we have ignored the issue of solving the various convex optimization problems.
- The first question is whether we should solve the **primal** or the **dual problem**.
- In the literature SVMs are usually trained in the dual.
- However, SVMs can be trained both in the primal and the dual – each approach has its advantages and disadvantages.
- It is not easy to create an efficient SVM solver, and often specialized appraoches have been developed, we only cover basic ideas here.

TRAINING SVM IN THE PRIMAL



Unconstrained formulation of soft-margin SVM:

$$\min_{\boldsymbol{\theta}, \theta_0} \quad \frac{\lambda}{2} \|\boldsymbol{\theta}\|^2 + \sum_{i=1}^{n} L\left(y^{(i)}, f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}\right)\right)$$

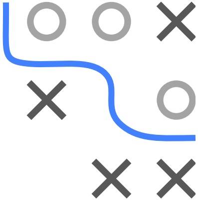
where $L(y, f) = \max(0, 1 - yf)$ and $f(\mathbf{x} \mid \boldsymbol{\theta}) = \boldsymbol{\theta}^T \mathbf{x} + \theta_0$.
(We inconsequentially changed the regularization constant.)

We cannot directly use GD, as the above is not differentiable.

Solutions:

1. Use smoothed loss (squared hinge, huber), then do GD.
   NB: Will not create a sparse SVM if we do not add extra tricks.
2. Use **subgradient** methods.
3. Do stochastic subgradient descent.
   Pegasos: Primal Estimated sub-GrAdient SOlver for SVM.

PEGASOS: SSGD IN THE PRIMAL



Approximate the risk by a stochastic 1-sample version:

$$\frac{\lambda}{2}\|\boldsymbol{\theta}\|^2 + L\left(y^{(i)}, f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}\right)\right)$$

With: $f(\mathbf{x} \mid \boldsymbol{\theta}) = \boldsymbol{\theta}^T\mathbf{x} + \theta_0$ and $L(y, f) = \max(0, 1 - yf)$
The subgradient for $\boldsymbol{\theta}$ is $\lambda\boldsymbol{\theta} - y^{(i)}\mathbf{x}^{(i)}\mathbb{I}_{yf<1}$

Stochastic subgradient descent (without intercept θ_0)

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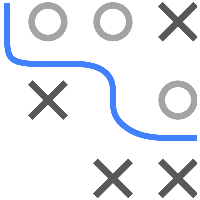
for $t = 1, 2, \ldots$ **do**
    Pick step size α
    Randomly pick an index i
    If $y^{(i)} f\left(\mathbf{x}^{(i)}\right) < 1$ set $\boldsymbol{\theta}^{[t+1]} = (1 - \lambda\alpha)\boldsymbol{\theta}^{[t]} + \alpha y^{(i)}\mathbf{x}^{(i)}$
    If $y^{(i)} f\left(\mathbf{x}^{(i)}\right) \geq 1$ set $\boldsymbol{\theta}^{[t+1]} = (1 - \lambda\alpha)\boldsymbol{\theta}^{[t]}$
end for

Note the weight decay due to the L2-regularization.

TRAINING SVM IN THE DUAL



The dual problem of the soft-margin SVM is

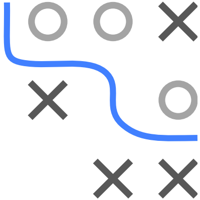
$$\max_\alpha \quad \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y^{(i)} y^{(j)} \left\langle \mathbf{x}^{(i)}, \mathbf{x}^{(j)} \right\rangle$$

$$\text{s.t.} \qquad 0 \leq \alpha_i \leq C \quad \sum_{i=1}^{n} \alpha_i y^{(i)} = 0$$

We could solve this problem using coordinate ascent. That means we optimize w.r.t. α_1, for example, while holding $\alpha_2, ..., \alpha_n$ fixed.

But: We cannot make any progress since α_1 is determined by $\sum_{i=1}^{n} \alpha_i y^{(i)} = 0$!

TRAINING SVM IN THE DUAL / 2



Solution: Update two variables simultaneously

$$\max_\alpha \quad \sum_{i=1}^n \alpha_i - \frac{1}{2}\sum_{i=1}^n\sum_{j=1}^n \alpha_i\alpha_j y^{(i)} y^{(j)} \left\langle \mathbf{x}^{(i)}, \mathbf{x}^{(j)} \right\rangle$$

$$\text{s.t.} \quad 0 \le \alpha_i \le C \quad \sum_{i=1}^n \alpha_i y^{(i)} = 0$$

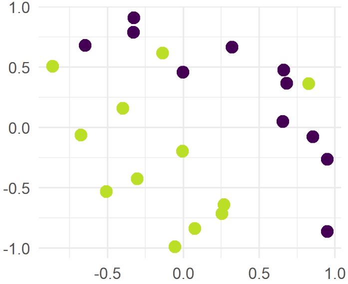
Pairwise coordinate ascent in the dual

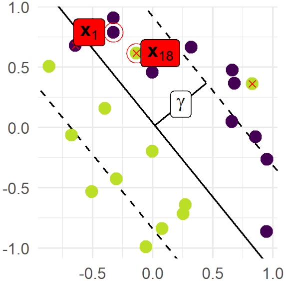
Initialize $\boldsymbol{\alpha} = 0$ (or more cleverly)
for $t = 1, 2, \ldots$ **do**
    Select some pair α_i, α_j to update next
    Optimize dual w.r.t. α_i, α_j, while holding α_k ($k \neq i, j$) fixed
end for

The objective is quadratic in the pair, and $s := y^{(i)}\alpha_i + y^{(j)}\alpha_j$ must stay constant. So both α are changed by same (absolute) amount, the signs of the change depend on the labels.

TRAINING SVM IN THE DUAL / 3

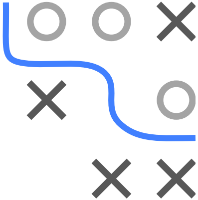
Assume we are in a valid state, $0 \leq \alpha_i \leq C$. Then we chose[1] two observations (encircled in red) for the next iteration. Note they have opposite labels so the sign of their change is equal.





[1] There are heuristics to pick the observations to speed up convergence.

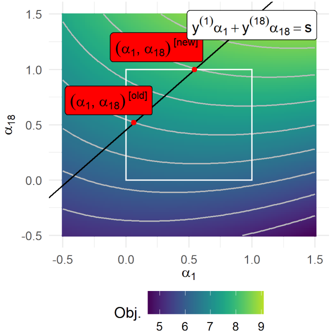
TRAINING SVM IN THE DUAL

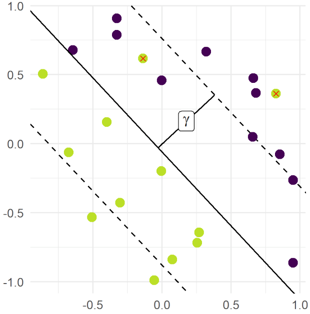


$$\max_\alpha \quad \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y^{(i)} y^{(j)} \left\langle \mathbf{x}^{(i)}, \mathbf{x}^{(j)} \right\rangle$$

$$\text{s.t.} \quad 0 \le \alpha_i \le C \quad \sum_{i=1}^{n} \alpha_i y^{(i)} = 0$$

We move on the linear constraint until the pair-optimum or the bounday (here: $C = 1$).





TRAINING SVM IN THE DUAL / 2

Sequential Minimal Optimization (SMO) exploits the fact that effectively we only need to solve a one-dimensional quadratic problem, over in interval, for which an analytical solution exists.