

Stochastic GD

take $|S|=B$ (mini batch)

$$\frac{1}{B} \sum_{i \in S} L'(y_i f(x_i; w)) y_i \nabla_w f(x_i; w)$$

SVM I

SVM:

- ① max margin predictors
- ② nonlinear SVM (via kernel)

Hard-margin SVM (training error zero)

Soft-margin SVM (training error nonzero)

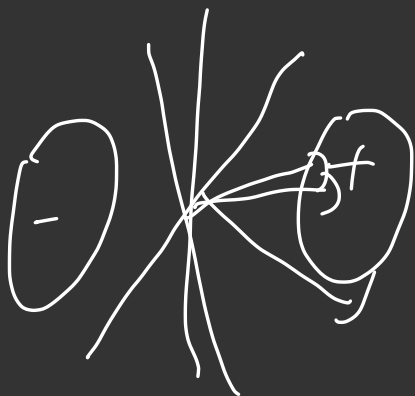
Nonlinear SVM kernels

Hard-Margin SVM

- Linear ~ separable data

$$\min \underbrace{y_i x_i^T w}_{\text{sign agree}} > 0$$

$$u \in \mathbb{R}^d$$



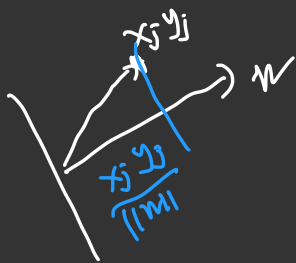
∞ bound

, we want the
max margin.

$$\min_i w^T x_i y_i > 0 \quad \leftarrow \text{we should normalize so we can't change margin by choosing } w.$$

$$\min_i \frac{w^T}{\|w\|} x_i y_i \quad \leftarrow \text{choose } w^T x_i y_i \geq 1$$

$$j = \arg \min_i y_i x_i^T w$$



$$\rightarrow \frac{1}{\|w\|}$$

$$\text{so } \begin{cases} \max & \frac{1}{\|w\|} \\ \text{subj.} & y_i x_i^T w \geq 1 \quad \forall i \end{cases}$$

$$\begin{cases} \min & \frac{1}{2} \|w\|^2 \quad (\text{convex}) \\ \text{subj to} & y_i x_i^T w \geq 1 \quad \forall i \quad (\text{convex set}) \end{cases}$$

Soft-margin SVM


Suppose the hard margin program

non-feasible.

Introduce slack variables $\xi_1 \dots \xi_n \geq 0$ $C > 0$ (tradeoff)

$$\begin{cases} \min & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \quad (\text{convex}) \\ \text{subj to} & y_i x_i^T w \geq 1 - \xi_i \quad \forall i \quad (\text{convex set}) \end{cases}$$

$\xi_i \geq 0$ for $i=1 \dots n$



Transform previous program to unconstrained
hinge loss

$$\min_{w \in \mathbb{R}^d} \frac{1}{2} \|w\|_2^2 + C \sum_{i=1}^n [1 - y_i x_i^T w]_+$$

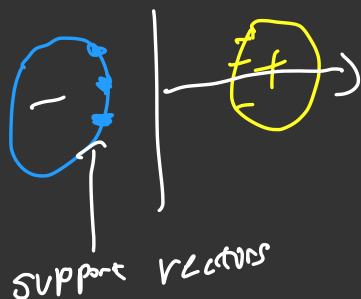
$$[a]_+ = \max\{0, a\} \text{ (ReLU)}$$

$$\left(\min_{w \in \mathbb{R}^d} \frac{1}{2} \|w\|_2^2 + C \sum_{i=1}^n \text{hinge}(y_i x_i^T w) \right)$$

$$\text{hinge}(z) = \max\{0, 1 - z\}$$

Each convex program has correlated dual program

Support Vectors



$$L(w, \alpha) = \frac{1}{2} \|w\|_2^2 + \sum_{i=1}^n \alpha_i (1 - y_i x_i^T w)$$

$$\underbrace{\sup_{\alpha \geq 0} L(w, \alpha)}_{p(w)} = \begin{cases} \frac{1}{2} \|w\|_2^2 & \forall i, w^T x_i y_i \geq 1 \text{ (feasible case)} \\ \infty & \text{(unfeasible case)} \end{cases}$$

$$\Rightarrow \arg \min_w p(w) = \arg \min_w \sup_{\alpha \geq 0} L(w, \alpha)$$

$$\sup_{\alpha \geq 0} \min_w L(w, \alpha)$$

$$D(\alpha) = \min_w L(w, \alpha) = \sum \alpha_i - \frac{1}{2} \left\| \sum_i \alpha_i y_i x_i \right\|^2$$

dual form