



Lagrange Multipliers & Duality of SVMs

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Most Slides are from Nick Rouzzi! Thanks Nick!!

The Strategy So Far...

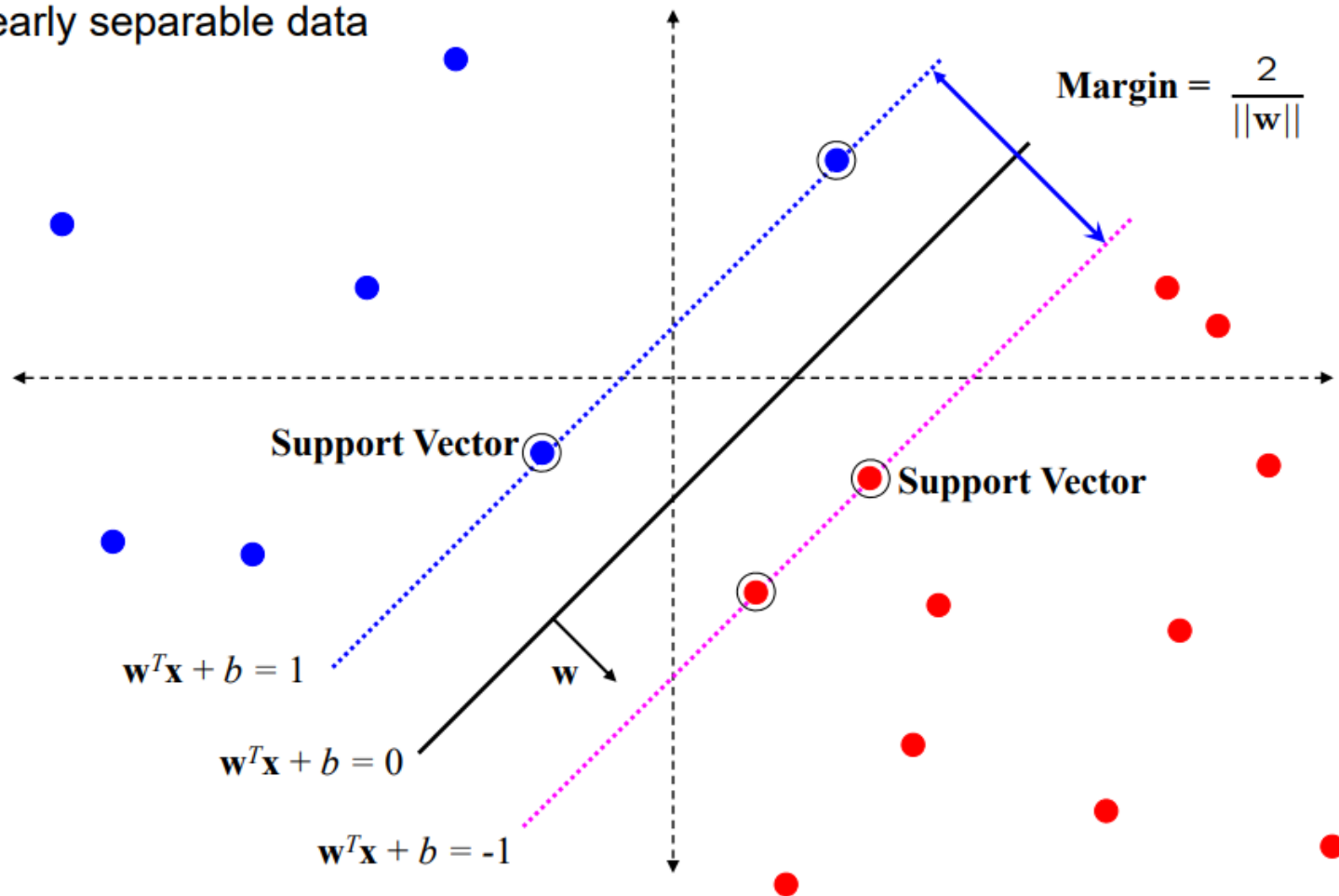


- Choose hypothesis space
- Construct loss function (ideally convex)
- Minimize loss to “learn” correct parameters

Recap: SVM



linearly separable data



- Recall: The SVM optimization problem:

$$\min_{w,b} \|w\|^2$$

such that

$$y^{(i)}(w^T x^{(i)} + b) \geq 1, \text{ for all } i$$

- This is a standard quadratic programming problem
 - Falls into the class of **convex optimization problems**
 - Can be solved with many specialized optimization tools (e.g., `quadprog()` in MATLAB)

A mathematical detour, we'll come back to SVMs soon!

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, & i &= 1, \dots, m \\ h_i(x) &= 0, & i &= 1, \dots, p \end{aligned}$$

Constrained Optimization



$$\min_{x \in \mathbb{R}^n} f_0(x)$$

f_0 is not necessarily convex

subject to:

$$\begin{aligned} f_i(x) &\leq 0, & i &= 1, \dots, m \\ h_i(x) &= 0, & i &= 1, \dots, p \end{aligned}$$

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, & i &= 1, \dots, m \\ h_i(x) &= 0, & i &= 1, \dots, p \end{aligned}$$

Constraints do not need to
be linear

Example



$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$x_1 + x_2 = 1$$

$$x_1 \geq 0$$

$$x_2 \geq 0$$

Example



$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$

$$-x_1 \leq 0$$

$$-x_2 \leq 0$$

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p \nu_i h_i(x)$$

- Incorporate constraints into a new objective function
- $\lambda \geq 0$ and ν are vectors of **Lagrange multipliers**
- The Lagrange multipliers can be thought of as enforcing soft constraints

Example



$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$

$$-x_1 \leq 0$$

$$-x_2 \leq 0$$

$$\begin{aligned} L(x_1, x_2, \nu_1, \lambda_1, \lambda_2) \\ = x_1 \log x_1 + x_2 \log x_2 + \nu_1 \cdot (1 - x_1 - x_2) - \lambda_1 x_1 - \lambda_2 x_2 \end{aligned}$$

- Construct a **dual function** by minimizing the Lagrangian over the primal variables

$$g(\lambda, \nu) = \inf_x L(x, \lambda, \nu)$$

- $g(\lambda, \nu) = -\infty$ whenever the Lagrangian is not bounded from below for a fixed λ and ν

Example



$$\min_{x \in \mathbb{R}^2} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$

$$-x_1 \leq 0$$

$$-x_2 \leq 0$$

Example



$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$

$$-x_1 \leq 0$$

$$-x_2 \leq 0$$

$$L(x_1, x_2, \nu_1, \lambda_1, \lambda_2)$$

$$= x_1 \log x_1 + x_2 \log x_2 + \nu_1 \cdot (1 - x_1 - x_2) - \lambda_1 x_1 - \lambda_2 x_2$$

Example



$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$

$$-x_1 \leq 0$$

$$-x_2 \leq 0$$

The Primal Problem



$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, & i &= 1, \dots, m \\ h_i(x) &= 0, & i &= 1, \dots, p \end{aligned}$$

Equivalently,

$$\inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

Why are these equivalent?

The Primal Problem



$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, & i &= 1, \dots, m \\ h_i(x) &= 0, & i &= 1, \dots, p \end{aligned}$$

Equivalently,

$$\inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

$$\sup_{\lambda \geq 0, \nu} \left[f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p \nu_i h_i(x) \right] = \infty$$

whenever x violates the constraints

$$\sup_{\lambda \geq 0, \nu} g(\lambda, \nu)$$

Equivalently,

$$\sup_{\lambda \geq 0, \nu} \inf_x L(x, \lambda, \nu)$$

- The dual problem is always concave, even if the primal problem is not convex
 - For each x , $L(x, \lambda, \nu)$ is a linear function in λ and ν
 - Minimum (or infimum) of linear functions is concave!

$$\sup_{\lambda \geq 0, \nu} \inf_x L(x, \lambda, \nu) \leq \inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

- Why?
 - $g(\lambda, \nu) \leq L(x, \lambda, \nu)$ for all x
 - $L(x', \lambda, \nu) \leq f_0(x')$ for any feasible x' , $\lambda \geq 0$
 - x is **feasible** if it satisfies all of the constraints
- Let x^* be the optimal solution to the primal problem and $\lambda \geq 0$

$$g(\lambda, \nu) \leq L(x^*, \lambda, \nu) \leq f_0(x^*)$$

Example: Solving the Dual Problem



$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$

$$-x_1 \leq 0$$

$$-x_2 \leq 0$$

More Examples



- Minimize $x^2 + y^2$ subject to $x + y \geq 1$
- Given a point $z \in \mathbb{R}^n$ and a hyperplane $w^T x + b = 0$, find the projection of the point z onto the hyperplane

- Under certain conditions, the two optimization problems are equivalent

$$\sup_{\lambda \geq 0, \nu} \inf_x L(x, \lambda, \nu) = \inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

- This is called **strong duality**
- If the inequality is strict, then we say that there is a **duality gap**
 - Size of gap measured by the difference between the two sides of the inequality

Slater's Condition



For any optimization problem of the form

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, & i &= 1, \dots, m \\ Ax &= b \end{aligned}$$

where f_0, \dots, f_m are **convex functions**, strong duality holds if there exists an x such that

$$\begin{aligned} f_i(x) &< 0, & i &= 1, \dots, m \\ Ax &= b \end{aligned}$$

$$\min_w \frac{1}{2} \|w\|^2$$

such that

$$y_i(w^T x^{(i)} + b) \geq 1, \text{ for all } i$$

- Note that Slater's condition holds as long as the data is linearly separable

$$L(w, b, \lambda) = \frac{1}{2} w^T w + \sum_i \lambda_i (1 - y_i (w^T x^{(i)} + b))$$

Convex in w , so take derivatives to form the dual

$$\frac{\partial L}{\partial w_k} = w_k + \sum_i -\lambda_i y_i x_k^{(i)} = 0$$

$$\frac{\partial L}{\partial b} = \sum_i -\lambda_i y_i = 0$$

$$L(w, b, \lambda) = \frac{1}{2}w^T w + \sum_i \lambda_i (1 - y_i(w^T x^{(i)} + b))$$

Convex in w , so take derivatives to form the dual

$$w = \sum_i \lambda_i y_i x^{(i)}$$

$$\sum_i \lambda_i y_i = 0$$

$$\max_{\lambda \geq 0} -\frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j x^{(i)T} x^{(j)} + \sum_i \lambda_i$$

such that

$$\sum_i \lambda_i y_i = 0$$

- By strong duality, solving this problem is equivalent to solving the primal problem
 - Given the optimal λ , we can easily construct w (b can be found by **complementary slackness...**)

Complementary Slackness



- Suppose that there is zero duality gap
- Let x^* be an optimum of the primal and (λ^*, v^*) be an optimum of the dual

$$\begin{aligned} f_0(x^*) &= g(\lambda^*, v^*) \\ &= \inf_x \left[f_0(x) + \sum_{i=1}^m \lambda_i^* f_i(x) + \sum_{i=1}^p v_i^* h_i(x) \right] \\ &\leq f_0(x^*) + \sum_{i=1}^m \lambda_i^* f_i(x^*) + \sum_{i=1}^p v_i^* h_i(x^*) \\ &= f_0(x^*) + \sum_{i=1}^m \lambda_i^* f_i(x^*) \\ &\leq f_0(x^*) \end{aligned}$$

Complementary Slackness



- This means that

$$\sum_{i=1}^m \lambda_i^* f_i(x^*) = 0$$

- As $\lambda \geq 0$ and $f_i(x_i^*) \leq 0$, this can only happen if $\lambda_i^* f_i(x^*) = 0$ for all i
- Put another way,
 - If $f_i(x^*) < 0$ (i.e., the constraint is not tight), then $\lambda_i^* = 0$
 - If $\lambda_i^* > 0$, then $f_i(x^*) = 0$
 - ONLY applies when there is no duality gap

Dual SVM (Obtaining b)



$$\max_{\lambda \geq 0} -\frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j x^{(i)T} x^{(j)} + \sum_i \lambda_i$$

such that

$$\sum_i \lambda_i y_i = 0$$

- By complementary slackness, $\lambda_i^* > 0$ means that $x^{(i)}$ is a support vector (can then solve for b using w)
- In particular,

$$b = y_i - w \cdot x_i$$

for any i where $\lambda_i > 0$

$$\max_{\lambda \geq 0} -\frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j x^{(i)T} x^{(j)} + \sum_i \lambda_i$$

such that

$$\sum_i \lambda_i y_i = 0$$

- Takes $O(n^2)$ time just to evaluate the objective function
 - Active area of research to try to speed this up