

4.1.7 Maximize: $f(x, y) = 16 - (x^2 + y^2)$.
subject to: $2x - y + 4 = 0$.

$$= L(x, y, \lambda) = 16 - (x^2 + y^2) + \lambda(2x - y + 4)$$

= Maximize over x & y :

$$\textcircled{1} \frac{\partial L}{\partial x} = -2x + 2\lambda = 0 \Rightarrow \boxed{\lambda = x}$$

$$\textcircled{2} \frac{\partial L}{\partial y} = -2y - \lambda = 0 \Rightarrow \boxed{y = -x/2}$$

= Substituting back in $L \Rightarrow$ dual function.

$$L(\lambda) = 16 - \left(\lambda^2 + \frac{\lambda^2}{4} \right) + \lambda \left(2\lambda + \frac{\lambda}{2} + 4 \right)$$

$$= 16 - \frac{5\lambda^2}{4} + \frac{5\lambda^2}{2} + 4\lambda = 16 + \frac{5\lambda^2}{4} + 4\lambda$$

= Minimize the dual function $L(\lambda)$

$$\frac{dL}{d\lambda} = \frac{5\lambda}{2} + 4 \Rightarrow \boxed{\lambda = -8/5}, \quad \frac{d^2L}{d\lambda^2} = \frac{5}{2} > 0 \text{ (minima)} \checkmark$$

= solution:

$$x = \lambda = \boxed{-8/5}, \quad y = -x/2 = \boxed{4/5}$$

= verification:

$$\textcircled{1} 2x - y + 4 = 0 \Rightarrow 2(-8/5) - 4/5 + 4 = \boxed{0} \checkmark$$

$$\textcircled{2} 16 - (x^2 + y^2) \Rightarrow 16 - (64/25 + 16/25) = 16 - 80/25 = 64/5 = \boxed{12.8}$$

4.4.7 Starting from equation 9n (4.17)

$$= L(w_1, w_2, b, \lambda) = \frac{w_1^2 + w_2^2}{2} + \sum_{i=1}^n \lambda_i (1 - z_i (w_1 x_i + w_2 y_i + b))$$

= From the partial derivative equations (4.18), we have:

• $w_1 = \sum_{i=1}^n \lambda_i \cdot z_i \cdot x_i$

• $w_2 = \sum_{i=1}^n \lambda_i \cdot z_i \cdot y_i$

• $\sum_{i=1}^n \lambda_i \cdot z_i = 0$

= This gives us $w = \sum_{i=1}^n \lambda_i \cdot z_i \cdot X_i$ where $X_i = (x_i, y_i)$

= Substituting this in the Lagrangian:

$$L(\lambda) = \frac{1}{2} \left(\sum_{i=1}^n \lambda_i \cdot z_i \cdot x_i \right)^2 + \frac{1}{2} \left(\sum_{i=1}^n \lambda_i \cdot z_i \cdot y_i \right)^2 + \sum_{i=1}^n \lambda_i - \sum_{i=1}^n \lambda_i \cdot z_i$$

= since $\sum_{i=1}^n \lambda_i \cdot z_i = 0$, the term with b vanishes. Quadratic terms combined as:

$$\frac{1}{2} \left(\sum_{i=1}^n \lambda_i \cdot z_i \cdot x_i \right)^2 + \frac{1}{2} \left(\sum_{i=1}^n \lambda_i \cdot z_i \cdot y_i \right)^2 = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \lambda_i \cdot \lambda_j \cdot z_i \cdot z_j (x_i x_j + y_i y_j)$$

$$L(\lambda) = \sum_{i=1}^n \lambda_i = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \lambda_i \cdot \lambda_j \cdot z_i \cdot z_j (X_i \cdot X_j)$$

4+2. 4.8.) (a) For a linear SVM, the scoring function from equation 4.22

$$= f(x) = \sum_i \lambda_i \cdot z_i (x_i \cdot x) + b.$$

= Since $x_i \cdot x = x_i x + y_i y$ for $x = (x, y)$ and $x_i = (x_i, y_i)$,

$$= f(x) = \left(\sum_i \lambda_i \cdot z_i \cdot x_i \right) x + \left(\sum_i \lambda_i \cdot z_i \cdot y_i \right) y + b.$$

= ∴ the weights are

$$x: w_1 = \sum_i \lambda_i \cdot z_i \cdot x_i.$$

$$y: w_2 = \sum_i \lambda_i \cdot z_i \cdot y_i.$$

(b) To reduce dimensionality using SVM weights:

- i. Features with larger $|w_j|$ values contribute more.
- ii. Eliminate features with weight below a threshold
- iii. The SVM can be retrained on feature set.