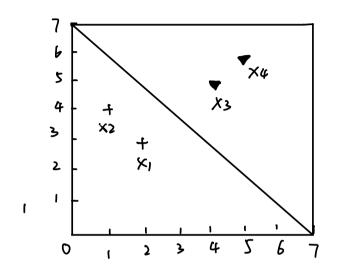
Q: (a) SVM

(i) odecision boundary



The denote $\chi_1(2,3)$ $\chi_2(1,4)$ $\chi_3(4,5)$ $\chi_4(5,6)$ we consider χ_1 χ_2 χ_3 are support vector we have $\lambda_1, \lambda_2, \lambda_3 \neq 0$

$$\binom{w_1}{w_2} = \lambda_1 \binom{2}{3} + \lambda_2 \binom{1}{4} - \lambda_3 \binom{4}{5}$$

$$(w_1 w_2)\binom{2}{3} + b = | \qquad (1)$$

$$(w_1 w_2)(\frac{1}{4}) + b = -1 \qquad (3)$$

$$(w_1 w_2)(\frac{4}{5}) + b = -1 \qquad (3)$$

$$c(1)(2)(3) \rightarrow w = (-\frac{1}{2}) \qquad b = \frac{7}{2}$$

$$-\frac{1}{2}\chi_1 - \frac{1}{2}\chi_2 + \frac{7}{2} = 0$$

$$\chi_1 + \chi_2 = 7$$

$$d = \frac{2}{||w||} = \frac{2}{||f| + \frac{1}{6}||} = 452$$

3 The linear decision boundary leads to max margin because SVM selects the hyperplane that max the distance between itself and the support vectors.

This is achieved by min IIwII resulting the widest margin = 2 11 min

Cil) Support vector: \$\famouslime{\chi(2,3)} \quad \chi_2(1,4) \quad \chi_3(4,5)\$

Reason O They Satisfy the Karush - kuhn-Tucker

Condition \quad \chi >6

O Removing or moving any one of them would

changle the optimal hyper-plane. Relocations XI would not.

(b) (i) O sharing parameters slashing memory

① much lower risk of over-fitting

③ retaining the receptive-field hierarchy

(ii) O Prevents Overfitting. By randomly omitting
ne wrons, the network canaot vely too heavily

on specific features, forcing it to learn more
robust and generalized representations

② Acts as ne Ensemble Method: During
trainning, different sub-networks are trained

D Data augmentation increases the diversity of training data, helping the model

generalize beter without reducing complexity

D Early stopping and dropout both reduce

model capacity, so they trade variance

for higher bins

due to the randomness of dropped neurons

(iii) Data augmentation