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NOMENCLATURE

X	training set
N	the number of training data
x_i	i-th training data
X_i	i-th data cluster
$\tilde{X}_i$	the other data clusters located on both sides of the i-th cluster center
w_i	weight vector of i-th cluster
b_i	bias of i-th cluster
k	the number of cluster
thr	threshold parameter
$e, \tilde{e}$	vectors of which elements are equal to 1
$q, \tilde{q}$	slack vectors
U_{ip}	membership degree of x_i to clusters p
$w, \tilde{w}$	weight vectors of hyperplanes
$b, \tilde{b}$	biases of hyperplanes
λ	a small positive scalar
L	A threshold parameter
α, β	lagrange coefficients
$c, \tilde{c}$	penalty parameter