MI-SVM maximizes the bag margin and realize the bag-level classification (Andrews et al., 2003). For a positive bag, the margin is defined by the "most positive" instance, i.e., the instance farthest from the hyperplane. However, the margin of a negative bag is defined by the "least negative" instance, i.e., the instance nearest to the hyperplane. Using the notion of a bag margin given above, we can define MI-SVM by

$$\min_{w,b,\oslash} \frac{1}{2}\|w\|^2 + C\sum_I \oslash_I \quad (4)$$

$$s.t.\ \forall I: Y_I(\langle w,x_i\rangle + b) \geq 1 - \oslash_I, \oslash_I \geq 0 \quad (5)$$

where w is the normal vector, C is the penalty parameter, $\oslash_I$ is the relaxation factor, Y_I are the bag labels, x_i is the instance, and b is the displacement. One can refer to the work by Andrew et al. (2003) for detailed formulation and pseudo-code of MI-SVM.

[1] Andrews S , Tsochantaridis I , Hofmann T . Support Vector Machines for Multiple-Instance Learning[J]. Advances in Neural Information Processing Systems, 2003, 15(2):561-568.