## $svm\_ward2025$

This program is parametrised by a classification dataset, with d features, split according to K-fold cross-validation. The superscript k is used to denote fold k and bars over the symbols are used to distinguish validation from training.

	Training	Validation	
Number of examples:	$n^k$	$ar{n}^k$	$\in \mathbb{N}$
Feature vectors:	$x_i^k$	$ar{x}_i^k$	$\in \mathbb{R}^d$
Labels:	$y_i^k$	$ar{y}_i^k$	$\in \{-1,+1\}$

The Radial Basis Function (RBF) kernel matrix gives a distance between every two examples j and j in fold k defined by

$$Q(\gamma)_{ij}^k := y_i^k y_j^k \exp\left(-\gamma ||x_i^k - x_j^k||^2\right). \tag{RBF}$$

The upper-level program is to choose hyperparameters C and  $\gamma$  that minimise the average over K folds of validation hinge loss error.

$$\begin{aligned} & \underset{C,\gamma,\zeta,\alpha}{\text{minimise}} & & \sum_{k=1}^K \frac{1}{\bar{n}^k} \sum_{i=1}^{\bar{n}^k} \zeta_i^k \\ & \text{subject to} & & C \geq 0, \\ & & & \gamma \geq 0, \\ & & & \zeta_i^k \geq 0 \\ & & & & \zeta_i^k \geq 1 - \sum_{j=1}^{n^k} \alpha_j^k \bar{Q}(\gamma)_{ij}^k - \bar{y}_i^k b^k \end{aligned} \end{aligned} \text{for } k = 1, \ldots, K, \\ & & \text{for } i = 1, \ldots, \bar{n}^k, \\ & & & \alpha^k \text{ solve (Dual-SVM)} \quad \text{for } k = 1, \ldots, K \quad \text{for } i = 1, \ldots, n^k.$$

The lower level problem is the Dual Support Vector Machine which aims to minimise the hinge loss training error while maximising the width of the margin.

For further details see [1, Section 4].

## References

[1] Samuel Ward, Alain Zemkoho, and Selin Ahipasaoglu. Mathematical programs with complementarity constraints and application to hyperparameter tuning for nonlinear support vector machines, 2025.