SVC API

sklearn.svm.SVC

class `sklearn.svm.SVC`(**, C=1.0, kernel='rbf', degree=3, gamma='scale', coef0=0.0, shrinking=True, probability=False, tol=0.001, cache_size=200, class_weight=None, verbose=False, max_iter=-1, decision_function_shape='ovr', break_ties=False, random_state=None*)

Parameters:

C - Regularization parameter.

Kernel - Specifies the kernel type to be used in the algorithm

Degree - Degree of the polynomial kernel function ('poly'). Ignored by all other kernels.

Gamma - Kernel coefficient for 'rbf', 'poly' and 'sigmoid'.

coef0 - Independent term in kernel function. It is only significant in 'poly' and 'sigmoid'.

Shrinking - Whether to use the shrinking heuristic.

Probability - Whether to enable probability estimates

class_weight - Whether we want to assign weights to our classes

max_iter - Limit on the number of iterations of the solver

decision_function_shape - One versus rest or one versus one method to solve in case of multi class classification

random_state - Numpy seed to be used while generating random numbers

Attributes

class_weight_ - Multipliers of parameter C for each class. Computed based on the `class_weight` parameter.

classes_ - Class labels

coef_ - Weights assigned to the features

dual_coef_ - Dual coefficients of the support vector in the decision function multiplied by their targets. For multiclass, coefficient for all 1-vs-1 classifiers.

fit_status_ 0 if correctly fitted, 1 otherwise (will raise warning)

intercept_ - Constants in decision function.

support_ - Indices of support vectors.

support_vectors_ - Support vectors.

n_support_ - Number of support vectors for each class.

Methods

`decision_function`(X)	Evaluates the decision function for the samples in X.
`fit`(X, y[, sample_weight])	Fit the SVM model according to the given training data.
`get_params`([deep])	Get parameters for this estimator.
`predict`(X)	Perform classification on samples in X.
`score`(X, y[, sample_weight])	Return the mean accuracy on the given test data and labels.
`set_params`(**params)	Set the parameters of this estimator.

How sklearn handles SVM?

- Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection.
- The advantages of support vector machines are:
  i. Effective in high dimensional spaces. ii. Still effective in cases where number of dimensions is greater than the number of samples.
  iii. Uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.
  iv. Versatile: different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.
- The disadvantages of support vector machines include:
  i. If the number of features is much greater than the number of samples, avoid over-fitting in choosing Kernel functions and regularization term is crucial.
  ii. SVMs do not directly provide probability estimates, these are calculated using an expensive five-fold cross-validation.
- The support vector machines in scikit-learn support both dense (numpy.ndarray and convertible to that by numpy.asarray) and sparse (any scipy.sparse) sample vectors as input.
- However, to use an SVM to make predictions for sparse data, it must have been fit on such data.
- For optimal performance, use C-ordered numpy.ndarray (dense) or scipy.sparse.csr_matrix (sparse) with dtype=float64.