

# Package ‘svmplus’

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**Type** Package

**Title** Implementation of Support Vector Machines Plus (SVM+)

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**Description** Implementation of Support Vector Machines Plus (SVM+) for classification problems. See (Vladimir et. al, 2009, <doi:10.1016/j.neunet.2009.06.042>) for theoretical details and see (Li et. al, 2016, <https://github.com/okbalefthanded/svmplus\_matlab>) for implementation details in 'MATLAB'.

**Depends** R (>= 2.15.0), quadprog, methods, Matrix, MASS

**License** GPL-3

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**LazyData** true

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SVMP

*Creates and returns an instance of the class specified in the svm\_type.*


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### Description

Creates and returns an instance of the class specified in the `svm_type`. In future, the current solver used for quadratic programming (`quadprog`) will be replaced by the equivalent `quadprog` solver defined in `CVXR` package. Also, `LIBSVM` and `LIBLINEAR` based faster implementations are planned to be supported.

### Usage

```
SVMP(cost = 1, gamma = 1, kernel_x = "rbf", degree_x = 3,
      gamma_x = 0.001, kernel_xstar = "rbf", degree_xstar = 3,
      gamma_xstar = 0.001, tol = 1e-05, svm_type = "QP")
```

### Arguments

<code>cost</code>	cost of constraints violation
<code>gamma</code>	parameter needed for privileged information
<code>kernel_x</code>	the kernel used for standard training data
<code>degree_x</code>	parameter needed for polynomial kernel for training data
<code>gamma_x</code>	parameter needed for rbf kernel for training data
<code>kernel_xstar</code>	the kernel used for privileged information (PI)
<code>degree_xstar</code>	parameter needed for polynomial kernel for PI
<code>gamma_xstar</code>	parameter needed for rbf kernel for PI
<code>tol</code>	tolerance of dual variables
<code>svm_type</code>	optimization techniques used: QP, LibSVM, LibLinear etc. Currently it supports only QP.

### Value

an instance of the class specified in the `svm_type`. Currently it supports only "QP", hence returns instance of the class `QPSvmPlus`. The return instance can be used to call `fit`, `project` and `predict` methods of the `QPSvmPlus`.

### Author(s)

Niharika Gauraha and Ola Spjuth

**Examples**

```
# This example is similar to the example given in the section 3.3 of the article:
# https://doi.org/10.1007/s10472-017-9541-2
```

```
#Generate train data
mean1 = rep(0, 2)
mean2 = rep(1, 2)
cov2 = cov1 = .5 * diag(2)
n = 20
X1 = mvrnorm(n, mean1, Sigma = cov1)
X2 = mvrnorm(n, mean2, Sigma = cov2)
X_train = rbind(X1, X2)
y_train = matrix(c(rep(1, n), rep(-1, n)), 2*n, 1)
# generate privileged information data
X1Star = matrix(0, n, 2)
X2Star = matrix(0, n, 2)
for(i in 1:n)
{
  X1Star[i, 1] = norm(X1[i,] - mean1, type = "2")
  X1Star[i, 2] = norm(X2[i,] - mean2, type = "2")
}
for(i in 1:n)
{
  X2Star[i, 1] = norm(X1[i, ] - mean2, type = "2")
  X2Star[i, 2] = norm(X2[i, ] - mean1, type = "2")
}
XStar = rbind(X1Star, X2Star)
# generate test data
n_test = 10
X1 = mvrnorm(n_test, mean1, Sigma = cov1)
X2 = mvrnorm(n_test, mean2, Sigma = cov2)
X_test = rbind(X1, X2)
y_test = matrix(c(rep(1, n_test), rep(-1, n_test)), 2*n_test, 1)
# create instance of the class type QP, using RBF kernel
qp = SVMP(cost = 100, gamma = .01,
          kernel_x = "rbf", gamma_x = .001,
          kernel_xstar = "rbf", gamma_xstar = .001,
          tol = .00001, svm_type = "QP")
# call the fit function
qp$fit(X_train, XStar, y_train)
# call the predict function
y_predict = qp$predict(X_test)
print(length(y_predict[y_predict == y_test]))
print("correct classification out of 20")

#using polynomial kernel
qp = SVMP(cost = 100, gamma = .01,
          kernel_x = "poly", degree_x = 3,
          kernel_xstar = "poly", gamma_xstar = 3,
          tol = .00001)
```

```

qp$fit(X_train, XStar, y_train)

y_predict = qp$predict(X_test)

print(length(y_predict[y_predict == y_test]))
print("correct classification out of 20")

#using linear kernel
qp = SVMP(cost = 10, gamma = .1,
          kernel_x = "linear",
          kernel_xstar = "linear",
          tol = .00001)

qp$fit(X_train, XStar, y_train)

y_predict = qp$predict(X_test)

print(length(y_predict[y_predict == y_test]))
print("correct classification out of 20")

```

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svmplus

*Implementation of SVM Plus*


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## Description

Implementation of SVM plus for classification problems.

## Details

The classical machine learning paradigm assumes, training examples in the form of iid pair:

$$(x_1, y_1), \dots, (x_l, y_l), \quad x_i \in X, \quad y_i \in \{-1, +1\}.$$

Training examples are represented as features  $x_i$  and the same feature space is required for predicting future observations. However, this approach does not make use of other useful data that is only available at training time; such data is referred to as Privileged Information (PI).

Learning Under Privileged Information (LUPI) is a novel machine learning paradigm. It offers faster convergence of the learning process by exploiting the privileged information. In other words, “fewer training examples are needed to achieve similar predictive performance” or “the same number of examples can provide a better predictive performance”. In LUPI paradigm, training examples come in the form of iid triplets

$$(x_1, x_1^*, y_1), \dots, (x_l, x_l^*, y_l), \quad x_i \in X, \quad x_i^* \in X^*, \quad y_i \in \{-1, +1\}$$

where  $x^*$  denotes PI. SVM+ is one realization of LUPI paradigm. In SVM+, privileged information is used to estimate a linear model of the slack variables, namely

$$\xi_i = (w^*)^T z_i^* + b^*,$$

where  $z_i = \phi(x_i)$  represents the kernel mapping.

The SVM+ objective function is defined as:

$$\min_{w,b} \left\{ \frac{1}{2} w^T w + \frac{\gamma}{2} (w^*)^T (w^*) + C \sum_{i=1}^l [(w^*)^T z_i^* + b^*] \right\}$$

$$s.t. \quad y_i (w^T z_i + b) \geq 1 - [(w^*)^T z_i^* + b^*],$$

$$(w^*)^T z_i^* + b^* \geq 0, \forall i$$

The dual SVM+ problem is defined as follow.

$$\max_{w,b} \left\{ \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \frac{1}{2\gamma} \sum_{i,j=1}^l (\alpha_i + \beta_i - C)(\alpha_j + \beta_j - C) K^*(x_i^*, x_j^*) \right\}$$

$$s.t. \quad \sum_{i=1}^l \alpha_i y_i = 0, \quad \sum_{i=1}^l (\alpha_i + \beta_i - C) = 0,$$

$$\alpha_i \geq 0, \quad \beta_i \geq 0$$

This package offers a Quadratic Programming (QP) based convex optimization solution for the dual SVM+ problem. In future, LIBSVM and LibLinear based faster implementations are planned to be supported. We refer to [1] for theoretical details of LUPI and SVM+, and we refer to [2] for implementation details of SVM+ in MATLAB.

## References

- [1] Vladimir et. al, Neural Networks, 2009, 22, pp 544–557. <https://doi.org/10.1016/j.neunet.2009.06.042>
- [2] Li et. al, 2016. [https://github.com/okbalefthanded/svplus\\_matlab](https://github.com/okbalefthanded/svplus_matlab)
- [3] Bendtsen, C., et al., Ann Math Artif Intell, 2017, 81, pp 155–166. <https://doi.org/10.1007/s10472-017-9541-2>

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