Package ‘RMTL’

October 12, 2022

Title  Regularized Multi-Task Learning
Type   Package
Version 0.9.9

Description Efficient solvers for 10 regularized multi-task learning algorithms applicable for regression, classification, joint feature selection, task clustering, low-rank learning, sparse learning and network incorporation. Based on the accelerated gradient descent method, the algorithms feature a state-of-art computational complexity O(1/k^2). Sparse model structure is induced by the solving the proximal operator. The detail of the package is described in the paper of Han Cao and Emanuel Schwarz (2018) <doi:10.1093/bioinformatics/bty831>.

Depends R (>= 3.5.0)

URL https://github.com/transbioZI/RMTL/

BugReports https://github.com/transbioZI/RMTL/issues/

Imports MASS (>= 7.3-50), psych (>= 1.8.4), corpcor (>= 1.6.9), doParallel (>= 1.0.14), foreach (>= 1.4.4)

Date 2022-04-29

License GPL-3

Encoding UTF-8

RoxygenNote 7.1.2

Suggests knitr, rmarkdown

VignetteBuilder knitr

NeedsCompilation no

Author Han Cao [cre, aut, cph],
     Emanuel Schwarz [aut]

Maintainer Han Cao <hank9cao@gmail.com>

Repository CRAN

Date/Publication 2022-05-02 16:10:09 UTC
RMTL-package

R topics documented:

RMTL-package ................................................................. 2
calcError ................................................................. 3
Create_simulated_data .................................................. 4
cvMTL ................................................................. 5
MTL ................................................................. 6
plot.cvMTL ........................................................... 8
plotObj ................................................................. 8
predict.MTL ........................................................... 9
print.MTL ............................................................. 10

Index 11

RMTL-package RMTL: Regularized Multi-Task Learning

Description

This package provides an efficient implementation of regularized multi-task learning (MTL) comprising 10 algorithms applicable for regression, classification, joint feature selection, task clustering, low-rank learning, sparse learning and network incorporation. All algorithms are implemented based on the accelerated gradient descent method and feature a complexity of $O(1/k^2)$. Parallel computing is allowed to improve the efficiency. Sparse model structure is induced by the solving the proximal operator.

Details

This package provides 10 multi-task learning algorithms (5 classification and 5 regression), which incorporate five regularization strategies for knowledge transferring among tasks. All algorithms share the same framework:

$$
\min_{W,C} \sum_{i}^t L(W_i, C_i | X_i, Y_i) + \lambda_1 \Omega(W) + \lambda_2 ||W||^2_F
$$

where $L(\cdot)$ is the loss function (logistic loss for classification or least square loss for linear regression), $\Omega(\cdot)$ is the cross-task regularization for knowledge transfer, and $||W||^2_F$ is used for improving the generalization. $X = \{X_i = n_i \times p | i \in \{1, ..., t\}\}$ and $Y = \{Y_i = n_i \times 1 | i \in \{1, ..., t\}\}$ are predictors matrices and responses of $t$ tasks respectively, while each task $i$ contains $n_i$ subjects and $p$ predictors. $W = p \times t$ is the coefficient matrix, where $W_i$, the $i$th column of $W$, refers to the coefficient vector of task $i$.

The function $\Omega(W)$ jointly modulates multi-task models($\{W_1, W_2, ..., W_t\}$) according to specific prior structure of $W$. In this package, 5 common regularization methods are implemented to incorporate different priors, i.e. sparse structure ($\Omega(W) = ||W||_1$), joint feature selection ($\Omega(W) = ||W||_{2,1}$), low-rank structure ($\Omega(W) = ||W||_*$), network-based relatedness across tasks ($\Omega(W) = ||WG||_F^2$), and task clustering ($\Omega(W) = tr(W^TW) - tr(F^TW^TW^TF)$). To call a specific method
correctly, the corresponding "short name" has to be given. Follow the above sequence of methods, the short names are defined: L21, Lasso, Trace, Graph and CMTL

For all algorithms, we implemented an solver based on the accelerated gradient descent method, which takes advantage of information from the previous two iterations to calculate the current gradient and then achieves an improved convergent rate. To solve the non-smooth and convex regularizer, the proximal operator is applied. Moreover, backward line search is used to determine the appropriate step-size in each iteration. Overall, the solver achieves a complexity of $O\left(\frac{1}{k^2}\right)$ and is optimal among first-order gradient descent methods.

For the academic references of the implemented algorithms, the users are referred to the paper (doi:10.1093/bioinformatics/bty831) or the vignettes in the package.

**calcError**

*Calculate the prediction error*

**Description**

Calculate the averaged prediction error across tasks. For classification problem, the miss-classification rate is returned, and for regression problem, the mean square error (MSE) is returned.

**Usage**

```r
calcError(m, newX = NULL, newY = NULL)
```

**Arguments**

- `m`: A MTL model
- `newX`: The feature matrices of new individuals
- `newY`: The responses of new individuals

**Value**

The averaged prediction error

**Examples**

```r
# create example data
data<-Create_simulated_data(Regularization="L21", type="Regression")
# train a model
model<-MTL(data$X, data$Y, type="Regression", Regularization="L21",
            Lam1=0.1, Lam2=0, opts=list(init=0, tol=10^-6, maxIter=1500))
# calculate the training error
calcError(model, newX=data$X, newY=data$Y)
# calculate the test error
calcError(model, newX=data$tX, newY=data$tY)
```
Create_simulated_data

Create an example dataset for testing the MTL algorithm

Description

Create an example dataset which contains 1), training datasets (X: feature matrices, Y: response vectors); 2), test datasets (tX: feature matrices, tY: response vectors); 3), the ground truth model (W: coefficient matrix) and 4), extra information for some algorithms (i.e. a matrix for encoding the network information is necessary for calling the MTL method with network structure(Regularization=Graph )

Usage

Create_simulated_data(
  t = 5,
  p = 50,
  n = 20,
  type = "Regression",
  Regularization = "L21"
)

Arguments

- **t** Number of tasks
- **p** Number of features
- **n** Number of samples of each task. For simplicity, all tasks contain the same number of samples.
- **type** The type of problem, must be "Regression" or "Classification"
- **Regularization** The type of MTL algorithm (cross-task regularizer). The value must be one of \{L21, Lasso, Trace, Graph, CMTL \}

Value

The example dataset.

Examples

data<-Create_simulated_data(t=5,p=50, n=20, type="Regression", Regularization="L21")
str(data)
**cvMTL**

*K-fold cross-validation*

**Description**

Perform the k-fold cross-validation to estimate the $\lambda_1$.

**Usage**

```r
cvMTL(
  X,
  Y,
  type = "Classification",
  Regularization = "L21",
  Lam1_seq = 10^seq(1, -4, -1),
  Lam2 = 0,
  G = NULL,
  k = 2,
  opts = list(init = 0, tol = 10^-3, maxIter = 1000),
  stratify = FALSE,
  nfolds = 5,
  ncores = 2,
  parallel = FALSE
)
```

**Arguments**

- **X**: A set of feature matrices
- **Y**: A set of responses, could be binary (classification problem) or continues (regression problem). The valid value of binary outcome $\in \{1, -1\}$
- **type**: The type of problem, must be Regression or Classification
- **Regularization**: The type of MTL algorithm (cross-task regularizer). The value must be one of \{L21, Lasso, Trace, Graph, CMTL\}
- **Lam1_seq**: A positive sequence of $\lambda_1$ which controls the cross-task regularization
- **Lam2**: A positive constant $\lambda_2$ to improve the generalization performance
- **G**: A matrix to encode the network information. This parameter is only used in the MTL with graph structure (Regularization=Graph)
- **k**: A positive number to modulate the structure of clusters with the default of 2. This parameter is only used in MTL with clustering structure (Regularization=CMTL) Note, the larger number is adapted to more complex clustering structure.
- **opts**: Options of the optimization procedure. One can set the initial search point, the tolerance and the maximized number of iterations through the parameter. The default value is list(init=0, tol=10^-3, maxIter=1000)
- **stratify**: stratify=TRUE is used for stratified cross-validation
MTL

The number of folds

The number of cores used for parallel computing with the default value of 2

parallel = TRUE is used for parallel computing

Value

The estimated $\lambda_1$ and related information

Examples

# create the example data
data <- Create_simulated_data(Regularization = "L21", type = "Classification")
# perform the cross validation
cvfit <- cvMTL(data$X, data$Y, type = "Classification", Regularization = "L21",
               Lam2 = 0, opts = list(init = 0, tol = 10^-6, maxIter = 1500), nfolds = 5,
               stratify = TRUE, Lam1_seq = 10^seq(1, -4, -1))
# show meta-information
str(cvfit)
# plot the CV accuracies across lam1 sequence
plot(cvfit)

MTL

Train a multi-task learning model.

Description

Train a multi-task learning model.

Usage

MTL(
  X,
  Y,
  type = "Classification",
  Regularization = "L21",
  Lam1 = 0.1,
  Lam1_seq = NULL,
  Lam2 = 0,
  opts = list(init = 0, tol = 10^-3, maxIter = 1000),
  G = NULL,
  k = 2
)
Arguments

X  A set of feature matrices

Y  A set of responses, could be binary (classification problem) or continues (regression problem). The valid value of binary outcome is \( \{1, -1\} \)

type  The type of problem, must be Regression or Classification

Regularization  The type of MTL algorithm (cross-task regularizer). The value must be one of \{L21, Lasso, Trace, Graph, CMTL \}

Lam1  A positive constant \( \lambda_1 \) to control the cross-task regularization

Lam1_seq  A positive sequence of Lam1. If the parameter is given, the model is trained using warm-start technique. Otherwise, the model is trained based on the Lam1 and the initial search point (opts$init).

Lam2  A non-negative constant \( \lambda_2 \) to improve the generalization performance with the default value of 0 (except for Regularization=CMTL)

opts  Options of the optimization procedure. One can set the initial search point, the tolerance and the maximized number of iterations using this parameter. The default value is list(init=0, tol=10^{-3}, maxIter=1000)

G  A matrix to encode the network information. This parameter is only used in the MTL with graph structure (Regularization=Graph)

k  A positive number to modulate the structure of clusters with the default of 2. This parameter is only used in MTL with clustering structure (Regularization=CMTL) Note, the larger number is adapted to more complex clustering structure.

Value

The trained model including the coefficient matrix \( W \) and intercepts \( C \) and related meta information

Examples

# create the example data
data<-Create_simulated_data(Regularization="L21", type="Regression")
# train a MTL model
# cold-start
model<-MTL(data$X, data$Y, type="Regression", Regularization="L21",
Lam1=0.1, Lam2=0, opts=list(init=0, tol=10^{-6}, maxIter=1500))
# warm-start
model<-MTL(data$X, data$Y, type="Regression", Regularization="L21",
Lam1=0.1, Lam1_seq=10^seq(-4, -1), Lam2=0, opts=list(init=0, tol=10^{-6}, maxIter=1500))
# meta-information
str(model)
# plot the historical objective values
plotObj(model)
plot.cvMTL

Plot the cross-validation curve

Description

Plot the cross-validation curve

Usage

## S3 method for class 'cvMTL'
plot(x, ...)

Arguments

x
The returned object of function cvMTL

... Other parameters

Examples

# create the example data
data<-Create_simulated_data(Regularization="L21", type="Classification")
# perform the cv
cvfit<-cvMTL(data$X, data$Y, type="Classification", Regularization=“L21”,
             Lam2=0, opts=list(init=0, tol=10^-6, maxIter=1500), nfolds=5,
             stratify=TRUE, Lam1_seq=10^seq(1,-4,-1))
# plot the curve
plot(cvfit)

plotObj

Plot the historical values of objective function

Description

Plot the values of objective function across iterations in the optimization procedure. This function indicates the “inner status” of the solver during the optimization, and could be used for diagnosis of the solver and training procedure.

Usage

plotObj(m)

Arguments

m A trained MTL model
Examples

# create the example data
data<-Create_simulated_data(Regularization="L21", type="Regression")
# Train a MTL model
model<-MTL(data$X, data$Y, type="Regression", Regularization="L21",
            Lam1=0.1, Lam2=0, opts=list(init=0, tol=10^-6, maxIter=1500))
# plot the objective values
plotObj(model)

predict.MTL

Predict the outcomes of new individuals

Description

Predict the outcomes of new individuals. For classification, the probability of the individual being assigned to positive label P(y==1) is estimated, and for regression, the prediction score is estimated.

Usage

## S3 method for class 'MTL'
predict(object, newX = NULL, ...)

Arguments

object A trained MTL model
newX The feature matrices of new individuals
... Other parameters

Value

The predictive outcome

Examples

# Create data
data<-Create_simulated_data(Regularization="L21", type="Regression")
# Train
model<-MTL(data$X, data$Y, type="Regression", Regularization="L21",
            Lam1=0.1, Lam2=0, opts=list(init=0, tol=10^-6, maxIter=1500))
predict(model, newX=data$tX)
print.MTL

Print the meta information of the model

Description

Print the meta information of the model

Usage

```r
## S3 method for class 'MTL'
print(x, ...)
```

Arguments

- `x` A trained MTL model
- `...` Other parameters

Examples

```r
# create data
data <- Create_simulated_data(Regularization="L21", type="Regression")
# train a MTL model
model <- MTL(data$X, data$Y, type="Regression", Regularization="L21",
             Lam1=0.1, Lam2=0, opts=list(init=0, tol=10^-6, maxIter=1500))
# print the information of the model
print(model)
```
Index

calcError, 3
Create_simulated_data, 4
cvMTL, 5

MTL, 6

plot.cvMTL, 8
plotObj, 8
predict.MTL, 9
print.MTL, 10

RMTL-package, 2