Package ‘miRNAss’

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Type Package

Title Genome-Wide Discovery of Pre-miRNAs with few Labeled Examples

Version 1.5

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Description Machine learning method specifically designed for pre-miRNA prediction. It takes advantage of unlabeled sequences to improve the prediction rates even when there are just a few positive examples, when the negative examples are unreliable or are not good representatives of its class. Furthermore, the method can automatically search for negative examples if the user is unable to provide them. MiRNAss can find a good boundary to divide the pre-miRNAs from other groups of sequences; it automatically optimizes the threshold that defines the classes boundaries, and thus, it is robust to high class imbalance. Each step of the method is scalable and can handle large volumes of data.

License Apache License 2.0

Encoding UTF-8

LazyData true

Imports Matrix, stats, Rcpp, CORElearn, RSpectra,

LinkingTo Rcpp

NeedsCompilation yes

RoxygenNote 6.0.1

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adjacencyMatrixKNN

MiRNAss: Genome-wide pre-miRNA discovery from few labeled examples

Description

This function builds the adjacency matrix (the graph) given a data frame of numerical features.

Usage

adjacencyMatrixKNN(sequenceFeatures, sequenceLabels = rep(0, nrow(sequenceFeatures)), nNearestNeighbor = 10, threadNumber = NA)

Arguments

sequenceFeatures
Data frame with features extracted from stem-loop sequences.

sequenceLabels
Vector of labels of the stem-loop sequences. It must have -1 for negative examples, 1 for known miRNAs and zero for the unknown sequences (the ones that would be classified).

nNearestNeighbor
Number of nearest neighbors in the KNN graph. The default value is 10.

threadNumber
Number of threads used for the calculations. If it is NA leave OpenMP decide the number (may vary across different platforms).

Value

Returns the eigen decomposition as a list with two elements: The eigen vectors matrix 'U' and the eigen values vector 'D'.

Examples

# First construct the label vector with the CLASS column
y = as.numeric(celegans$CLASS)*2 - 1

# Remove some labels to make a test
y[sample(which(y>0),200)] = 0
y[sample(which(y<0),700)] = 0

# Take all the features but remove the label column
x = subset(celegans, select = -CLASS)

A = adjacencyMatrixKNN(x, y, 10, 8)

for (nev in seq(50,200, 50)) {
    # the data frame of features 'x' should not be pass as parameter
    p = miRNAss(sequenceLabels = y, AdjMatrix = A,
                nEigenVectors = nev)
# Calculate some performance measures
SE = mean(p[celegans$CLASS & y==0] > 0)
SP = mean(p[!celegans$CLASS & y==0] < 0)
cat("N: ", nev, "\n SE: ", SE, "\n SP: ", SP, "\n")

---

**celegans**

*Features extracted from hairpins of Caenorhabditis elegans.*

**Description**

Small dataset of features extracted from C. elegans hairpins. The full dataset is contained in the zip file "experiment_scripts.zip" that can be downloaded from:

**Usage**

`celegans`

**Format**

A data frame with 1000 rows and 29 columns. The first 28 columns are numeric features used in [1]. The last column is a logical variable indicating if the stem-loop is a pre-miRNA or not.

**Details**


**References**

http://sourceforge.net/projects/sourcesinc/files/mirnass/

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**eigenDecomposition**

*MiRNAss: Genome-wide pre-miRNA discovery from few labeled examples*

**Description**

This function calculates the eigenvectors and eigen values of the Laplacian of the graph. As this process is quite time consuming, this function allows to obtain this decomposition once and the be able to run miRNAss several times in shorter times.

**Usage**

`eigenDecomposition(AdjMatrix, nEigenVectors)`
**Arguments**

AdjMatrix    Adjacency sparse matrix of the graph.
nEigenVectors    Number of eigen vectors.

**Value**

Returns the eigen decomposition as a list with two elements: The eigen vectors matrix 'U' and the eigen values vector 'D'.

**Examples**

```r
# First construct the label vector with the CLASS column
y = as.numeric(celegans$CLASS)*2 - 1

# Remove some labels to make a test
y[sample(which(y>0),200)] = 0
y[sample(which(y<0),700)] = 0

# Take all the features but remove the label column
x = subset(celegans, select = -CLASS)

A = adjacencyMatrixKNN(x, y, 10, 8)
E = eigenDecomposition(AdjMatrix = A, nEigenVectors = 100)
for (mp in c(0.1,1,10)) {
  p = miRNAss(sequenceLabels = y, AdjMatrix = A,
              eigenVectors = E, missPenalization = mp)
  # Calculate some performance measures
  SE = mean(p[ celegans$CLASS & y==0] > 0)
  SP = mean(p[!celegans$CLASS & y==0] < 0)
  cat("mP: ", mp, "\n SE: ", SE, "\n SP: ", SP, "\n")
}
```

**Description**

This is the main function of the miRNAss package and implements the miRNA prediction method. It takes as main parameters a matrix with numerical features extracted from RNA hairpins and an incomplemt vector of labels where the positive number represents known miRNAs, the negative are not-miRNA hairpins and te zero values are unknown sequences (those that will be classified). As a results it returns a complete label vector.
miRNAss

Usage

miRNAss(sequenceFeatures = NULL, sequenceLabels, AdjMatrix = NULL, nNearestNeighbor = 10, missPenalization = 1, scalingMethod = "relief", thresholdObjective = "Gm", neg2label = 0.05, positiveProp = NULL, eigenVectors = NULL, nEigenVectors = min(400, round(length(sequenceLabels)/5)), threadNumber = NA)

Arguments

sequenceFeatures
   Data frame with features extracted from stem-loop sequences. It is not required if the adjacency matrix is provided.

sequenceLabels
   Vector of labels of the stem-loop sequences. It must have -1 for negative examples, 1 for known miRNAs and zero for the unknown sequences (the ones that would be classified).

AdjMatrix
   Sparse adjacency matrix representing the graph. If sequence features are provided it is ignored.

nNearestNeighbor
   Number of nearest neighbors in the KNN graph. The default value is 10.

missPenalization
   Penalization of the misclassification of known examples. The default value is 1. If the examples are not very confident, this value can be diminished.

scalingMethod
   Method used for normalization and scaling of the features. The options are 'none', 'whitening' and 'relief' (the default option). The first option does nothing, the second calls the built-in function 'scale' and the last one uses the ReliefFexpRank algorithm from the coreLearn package.

thresholdObjective
   Performance measure that would be optimized when estimating the threshold. The options are 'Gm' (geometric mean of the SE and the SP), 'G' (geometric mean of the SE and the precision), 'F1' (harmonic mean between SE and the precision) and 'none' (do not calculate any threshold). The default value is 'Gm'.

neg2label
   Proportion of unlabeled stem-loops that would be labeled as negative with the automatic method to start the classification algorithm. The default is 0.05.

positiveProp
   Expected proportion of positive sequences. If it is not provided by the user, is estimated as sum(y > 0) / sum(y != 0) when there are negative examples or as 2 * sum(y > 0) / sum(y == 0) when not.

eigenVectors
   Eigen decomposition of the Laplacian matrix, as returned by the function eigenDecomposition. If it is not provided it is calculated internally (this parameter allows to calculate the eigen vectors once and then run several times miRNAss with the same eigen vectors).

nEigenVectors
   Number of eigen vectors used to approximate the solution of the optimization problem. If the number is too low, smoother topographic solutions are founded, probably losing SP but achieving a better SE. Generally, 400 are enough.

threadNumber
   Number of threads used for the calculations. If it is NA leave OpenMP decide the number (may vary across different platforms).
Value

Returns a vector with the same size of the input vector y with the prediction scores for all sequences (even the labelled examples). If a threshold Objective different from 'none' was set, the threshold is estimated and subtracted from the scores, therefore the new threshold that divide the classes is zero. Also, the positive scores are divided by the max positive score, and the negative scores are divided by the magnitude of the minimum negative score.

Examples

# First construct the label vector with the CLASS column
y = as.numeric(celegans$CLASS)*2 - 1

# Remove some labels to make a test
y[sample(which(y>0),200)] = 0
y[sample(which(y<0),700)] = 0

# Take all the features but remove the label column
x = subset(celegans, select = -CLASS)

# Call miRNAss with default parameters
p = miRNAss(x,y)

# Calculate some performance measures
SE = mean(p[ celegans$CLASS & y==0] > 0)
SP = mean(p[!celegans$CLASS & y==0] < 0)
cat("Sensitivity: ", SE, " Specificity: ", SP, "\n")
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