

# Package ‘MDMICA’

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**Title** Independent Component Analysis via Mutual Dependence Measures

**Version** 1.0.0

**Date** 2018-01-30

**Description** Implementation of independent component analysis methods based on mutual dependence measures in Jin, Z., and Matteson, D. S. (2017) <https://arxiv.org/abs/1709.02532> and Pfister, N., et al. (2018) [doi:10.1111/rssb.12235](https://doi.org/10.1111/rssb.12235).

**Depends** R (>= 3.4.0)

**Imports** energy (>= 1.7-2),  
MDMeasure (>= 1.0.0),  
dHSIC (>= 2.0),  
rBayesianOptimization (>= 1.1.0)

**Suggests** testthat (>= 2.0.0)

**License** GPL (>= 2)

**LazyData** true

**RoxygenNote** 6.0.1

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MDMICA-package	<i>Independent Component Analysis via Mutual Dependence Measures</i>
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## Description

MDMICA: A package for independent component analysis via mutual dependence measures

## Details

The MDMICA package provides independent component analysis methods based on mutual dependence measures.

### Applying mutual dependence measures

The mutual dependence measures include:

- distance-based energy statistics
  - asymmetric measure  $\mathcal{R}_n$  based on distance covariance  $\mathcal{V}_n$
  - symmetric measure  $\mathcal{S}_n$  based on distance covariance  $\mathcal{V}_n$
  - simplified complete measure  $\mathcal{Q}_n^*$  based on incomplete V-statistics
- kernel-based maximum mean discrepancies
  - d-variable Hilbert–Schmidt independence criterion  $\text{dHSIC}_n$  based on Hilbert–Schmidt independence criterion  $\text{HSIC}_n$

### Initializing local optimization methods

The initialization methods include:

- Latin hypercube sampling
- Bayesian optimization

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mdm\_ica

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*Independent Component Analysis via Mutual Dependence Measures*


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### Description

mdm\_ica performs independent component analysis by minimizing mutual dependence measures of all univariate components in  $\mathbf{X}$ .

### Usage

```
mdm_ica(X, num_lhs = NULL, mdm_type = "comp", num_bo = NULL,
        kernel = "exp", opt_algo = "par")
```

### Arguments

<code>X</code>	A matrix or data frame, where rows represent samples, and columns represent components.
<code>num_lhs</code>	The number of points generated by Latin hypercube sampling. If omitted, an adaptive number is used.
<code>mdm_type</code>	The type of mutual dependence measures, including <ul style="list-style-type: none"> <li>• <code>asym</code>: asymmetric measure <math>\mathcal{R}_n</math> based on distance covariance <math>\mathcal{V}_n</math>;</li> <li>• <code>sym</code>: symmetric measure <math>\mathcal{S}_n</math> based on distance covariance <math>\mathcal{V}_n</math>;</li> <li>• <code>comp</code>: simplified complete measure <math>\mathcal{Q}_n^*</math> based on incomplete V-statistics;</li> <li>• <code>dhsic</code>: d-variable Hilbert–Schmidt independence criterion <math>\text{dHSIC}_n</math> based on Hilbert–Schmidt independence criterion <math>\text{HSIC}_n</math>.</li> </ul>
<code>num_bo</code>	The number of points evaluated by Bayesian optimization.

kernel	<p>The kernel of the underlying Gaussian process in Bayesian optimization, including</p> <ul style="list-style-type: none"> <li>• exp: squared exponential kernel;</li> <li>• mat: Matern 5/2 kernel.</li> </ul>
opt_algo	<p>The algorithm of optimization, including</p> <ul style="list-style-type: none"> <li>• def: deflation algorithm, where the components are extracted one at a time;</li> <li>• par: parallel algorithm, where the components are extracted simultaneously.</li> </ul>

## Value

mdm\_ica returns a list including the following components:

theta	The rotation angles of the estimated unmixing matrix.
W	The estimated unmixing matrix.
obj	The objective value of the estimated independence components.
S	The estimated independence components.

## References

- Jin, Z., and Matteson, D. S. (2017). Generalizing Distance Covariance to Measure and Test Multivariate Mutual Dependence. arXiv preprint arXiv:1709.02532. <https://arxiv.org/abs/1709.02532>.
- Pfister, N., et al. (2018). Kernel-based tests for joint independence. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 80(1), 5-31. <http://dx.doi.org/10.1111/rssb.12235>.

## Examples

```
# X is a 10 x 3 matrix with 10 samples and 3 components
X <- matrix(rnorm(10 * 3), 10, 3)

# deflation algorithm
mdm_ica(X, mdm_type = "asym", opt_algo = "def")
# parallel algorithm
mdm_ica(X, mdm_type = "asym", opt_algo = "par")

## Not run:
# bayesian optimization with exponential kernel
mdm_ica(X, mdm_type = "sym", num_bo = 1, kernel = "exp", opt_algo = "par")
# bayesian optimization with matern kernel
mdm_ica(X, mdm_type = "comp", num_bo = 1, kernel = "mat", opt_algo = "par")

## End(Not run)
```

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