



MAX PLANCK INSTITUTE  
FOR DYNAMICS OF COMPLEX  
TECHNICAL SYSTEMS  
MAGDEBURG



COMPUTATIONAL METHODS IN  
SYSTEMS AND CONTROL THEORY

# MOR Software

(Co-Developed in the CSC Group)

C. Himpe, P. Mlinarić, J. Saak, S.W.R. Werner

CSC Seminar

2021–05–18



1. emgr
2. hapod
3. morgen
4. M-M.E.S.S.
5. MORLAB
6. SOLBT
7. SOMDDPA
8. pyMOR

emgr

- Authors: C. Himpe
- Version: 5.9 (2021-01-21)
- License: BSD-2-Clause
- Website: <https://gramian.de>



$$\begin{aligned}\dot{x} &= f(x, u, \theta, t) \\ y &= g(x, u, \theta, t)\end{aligned}$$

- Language: MATLAB & Octave (600 LoC)
- Type: back-end library
- Started: 2012
- Paper: C. Himpe: emgr – The Empirical Gramian Framework;  
Algorithms 11(7): 91, 2018. doi:10.3390/a11070091



## Empirical Gramians:

- Empirical Controllability Gramian
- Empirical Observability Gramian
- Empirical Cross Gramian
- Empirical Linear Cross Gramian
- Empirical Sensitivity Gramian (Parameter Controllability)
- Empirical Identifiability Gramian (Parameter Observability)
- Empirical Joint Gramian (Parameter Observability & State Minimality)

## Advanced Features:

- Custom integrator / solver
- Custom inner product / kernel
- Partitioned cross Gramian / joint Gramian



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# emgr: Applications

- Model Reduction
  - Nonlinear Model Order Reduction
  - Parametric Model Order Reduction
  - Combined State and Parameter Reduction
  - Dynamic Mode Decomposition
- Decentralized Control
- Sensitivity Analysis
- Parameter Identification
- Nonlinearity Quantification
- Uncertainty Quantification
- Optimal Placement
- System Norms & Indices
- Matrix Equations
- Tau Functions

hapod

- Authors: C. Himpe & S. Rave
- Version: 3.2 (2021-05-05)
- License: BSD-2-Clause
- Website: <https://git.io/hapod>

$$X = U\Sigma(V)$$

- Language: MATLAB & Octave (300 LoC)
- Type: drop-in function
- Started: 2016
- Paper: C. Himpe, T. Leibner, S. Rave: **Hierarchical Approximate Proper Orthogonal Decomposition**; SIAM Journal on Scientific Computing 40(5): A3267–A3292, 2018. doi:10.1137/16M1085413



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hapod: Features

## Algorithm Features:

- Error-driven computation
- Column-wise partitioned data
- Incremental and distributed topology
- Rigorous POD-of-PODs
- Single-pass algorithm
- Minimal Communication
- Custom SVD back-ends
- MAPREDUCE ready

**BTW:** Combined, emgr and hapod enable low-rank empirical cross Gramians.

## Large-Scale ...

- Proper Orthogonal Decomposition (POD)
- Singular Value Decomposition (SVD)
- Principal Component Analysis (PCA)
- Empirical Orthogonal Functions (EOF)
- Karhunen-Loeve Transformation (KLT)
- Empirical Eigenfunctions (EEF)
- Unsupervised Learning (UL)
- Data Compression / Dimension Reduction (in general)

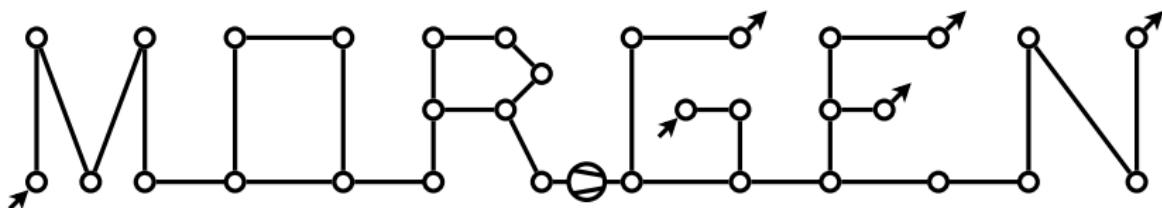
## In ...

- Memory-limited settings (single board computers)
- Distributed memory settings (super computers)

morgen



- Authors: C. Himpe & S. Grundel
- Version: 0.99 (2021-04-12)
- License: BSD-2-Clause
- Website: <https://git.io/morgen>



- Language: MATLAB & Octave (6000 LoC)
- Type: test platform for gas, water, and district-heating networks
- Started: 2016
- Paper: C. Himpe, S. Grundel, P. Benner: **Model Order Reduction for Gas and Energy Networks**; arXiv math.OC: 2011.12099, 2021. arXiv:2011.12099



## Design Principles:

- Modular
- Configurable
- Extensible

## Modules:

- 2 Models (discretizations)
- 4 Solvers (time steppers)
- 23 Reductors (structured & projection-based, emgr back-end included)
- >20 Networks (topologies and scenarios)
- >20 Tests (simulation and reduction)

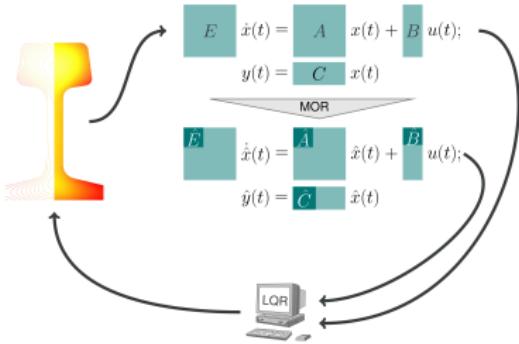


- Testing model-solver-reductor combinations
- Comparing models, solvers and reductors
- Benchmarking reductors
- Uncertainty quantification
- Prototyping algorithms

## Gas networks are ...

- high-dimensional, hyperbolic, parametric, and nonlinear;
- and thus a real-life model reduction challenge.

M-M.E.S.S.



- All equations are associated to a possibly abstract **standard state-space system**  $\Sigma(\mathbf{E}, \mathbf{A}, \mathbf{B}, \mathbf{C})$  or its dual.
- Proper differential-algebraic equations (DAE) or second-order (SO) systems use **implicit index-reduction** or **implicit linearization** to achieve this.
- The transformed implicit systems are (preferably) never formed explicitly.
- Operations with systems are abstracted into **user-supplied functions sets (USFS)**:

USFS	default	so_1 / so_2	dae_1	dae_2	dae_1/2/3_so
System	standard / generalized state-space form	second-order 1st/2nd companion form	index-1 DAE	index-2 Stokes-type DAEs	second-order index-1/2/3 using companion form
Demos	FDM, Rail	TripleChain	DAE1 (BIPS Power-systems model)	DAE2 Kármán vortex shedding	constrained TripleChain

$$0 = \mathbf{A}^T \mathbf{X} + \mathbf{X} \mathbf{A} + \mathbf{C}^T \mathbf{C} - \mathbf{X} \mathbf{B} \mathbf{B}^T \mathbf{X}$$

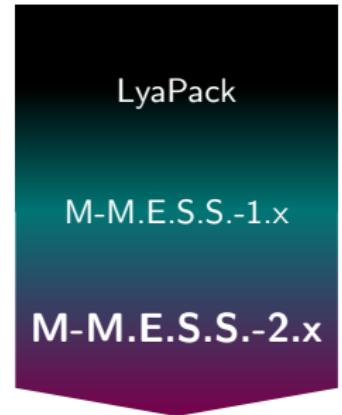
$$0 = \mathbf{A}^T \mathbf{X} \mathbf{E} + \mathbf{E}^T \mathbf{X} \mathbf{A} + \mathbf{C}^T \mathbf{C}$$

$$0 = \mathbf{A}^T \mathbf{X} \mathbf{E} + \mathbf{E}^T \mathbf{X} \mathbf{A} + \mathbf{C}^T \mathbf{C} - \mathbf{E}^T \mathbf{X} \left( \mathbf{B}_1 \mathbf{B}_1^T - \mathbf{B}_2 \mathbf{B}_2^T \right) \mathbf{X} \mathbf{E}$$

$$\mathbf{E}^T \dot{\mathbf{X}}(t) \mathbf{E} = \mathbf{A}^T \mathbf{X}(t) \mathbf{E} + \mathbf{E}^T \mathbf{X}(t) \mathbf{A} + \mathbf{C}^T \mathbf{C} - \mathbf{E}^T \mathbf{X}(t) \mathbf{B} \mathbf{B}^T \mathbf{X}(t) \mathbf{E}$$

$$\mathbf{E}(t)^T \dot{\mathbf{X}}(t) \mathbf{E}(t) = \left( \mathbf{A}(t) + \dot{\mathbf{E}}(t) \right)^T \mathbf{X}(t) \mathbf{E}(t) + \mathbf{E}(t)^T \mathbf{X}(t) \left( \mathbf{A}(t) + \dot{\mathbf{E}}(t) \right) + \mathbf{C}(t)^T \mathbf{C}(t) - \mathbf{E}(t)^T \mathbf{X}(t) \mathbf{B}(t) \mathbf{B}(t)^T \mathbf{X}(t) \mathbf{E}(t)$$

$$0 = \mathbf{A}^T \mathbf{X} \mathbf{E} + \mathbf{E}^T \mathbf{X} \mathbf{A} + \sum_k \mathbf{N}_k^T \mathbf{X} \mathbf{N}_k + \mathbf{C}^T \mathbf{C}$$



Algebraic Riccati equations  $\mathcal{R}(X) = 0$ :

$$\boxed{A^T} \quad X \quad + \quad X \quad \boxed{A} \quad - \quad X \quad \boxed{BB^T} \quad X \quad + \quad \boxed{C^T C} = 0$$

where  $A \in \mathbb{R}^{n \times n}$  (sparse),  $B \in \mathbb{R}^{n \times m}$ , and  $C \in \mathbb{R}^{n \times p}$  with  $m, p \ll n$  and  $n$  “large”.

Common solution paradigm: compute low-rank approximation:

$$X \approx z \begin{bmatrix} z^T \\ D \\ z^T \end{bmatrix} \quad \text{or} \quad X \approx z \begin{bmatrix} D \\ z^T \end{bmatrix}$$

## Balanced Truncation

- `mess_balanced_truncation`
- `mess_balanced_truncation_bilinear`
- BT Demos in Rail and FDM folders

## Balanced Truncation for structured (DAE) systems

- Second order: BT Demos in Triplechain folder
- First order DAEs: BT Demos in DAE\_1 and DAE\_2 folders
- Second order DAEs: BT Demos in DAE\_2\_SO and DAE\_3\_SO folders  
(DAE\_1\_SO following as soon as moderate size model is found)

## Interpolatory MOR (theoretically all supported system classes)

- `mess_tangential_irka`

For Riccati-based BT methods: see [ModRed 2019 book chapter](#)

## M-M.E.S.S.-2.1 — facts &amp; figures:

# contributors:	≈ 15
# code lines:	≈ 18 500 (≈ 26 000 including CI tests)
# comment and help lines:	≈ 12 000 (≈ 13 000 including CI tests)
history:	more than 10 years of active development
license:	BSD 2-Clause

## Benchmarks

Fishtail	BT, second-order, ≈780k DoFs
Adaptive Spindle support	BT, second-order index-1, ≈250k DoFs
Bilinear Rail	BT, bilinear, ≈ 5k DoFs



E-Mail	<a href="mailto:mess@mpi-magdeburg.mpg.de">mess@mpi-magdeburg.mpg.de</a>
WWW	<a href="https://www.mpi-magdeburg.mpg.de/projects/mess">https://www.mpi-magdeburg.mpg.de/projects/mess</a>
MPI	<a href="https://gitlab.mpi-magdeburg.mpg.de/mess/mmess-releases">GITLab</a>
Github	<a href="https://github.com/mpimd-csc/mmess">Github</a>
Zenodo	<a href="https://doi.org/10.5281/zenodo.3368844">Zenodo</a>

**MORLAB**



## MORLAB (Model Order Reduction LABoratory)

- (dense) model reduction in MATLAB/Octave
- based on spectral projection methods

<https://www.mpi-magdeburg.mpg.de/projects/morlab>

- Authors: P. Benner, S. W. R. Werner
- Version: 5.0 (2019-08-23)
- License: GNU AGPL v3.0+
- Started: 2006
- Dependencies: MATLAB ( $\geq$  2012b); Octave ( $\geq$  4.0.0)
- Paper: P. Benner, and S. W. R. Werner:  
**MORLAB – The Model Order Reduction LABoratory**,  
e-print 2002.12682, arXiv, 2020, <https://arxiv.org/abs/2002.12682>



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# MORLAB: Model reduction features

- modal truncation
- balanced truncation
- limited balanced truncation
- LQG balanced truncation
- $\mathcal{H}_\infty$  balanced truncation
- balanced stochastic truncation
- positive-real balanced truncation
- bounded-real balanced truncation
- Hankel-norm approximation
- second-order balanced truncation
- limited second-order balanced truncation

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- balanced truncation
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- balanced stochastic truncation
- positive-real balanced truncation
- bounded-real balanced truncation
- Hankel-norm approximation
- second-order balanced truncation
- limited second-order balanced truncation

### Standard systems

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t), \\ y(t) &= Cx(t) + Du(t)\end{aligned}$$

### Descriptor systems

$$\begin{aligned}E\dot{x}(t) &= Ax(t) + Bu(t), \\ y(t) &= Cx(t) + Du(t)\end{aligned}$$

### Second-order systems

$$\begin{aligned}M\ddot{x}(t) &= -E\dot{x}(t) - Kx(t) + B_u u(t), \\ y(t) &= C_p x(t) + C_v \dot{x}(t) + Du(t)\end{aligned}$$

## Matrix equation solvers

Lyapunov equations

$$AXE^T + EXA^T + BB^T = 0,$$

$$AXA^T - EXE^T + BB^T = 0$$

Sylvester equations

$$AXE + FXB + C = 0$$

Bernoulli equations

$$A^T X E + E^T X A - E^T X B B^T X E = 0$$

Riccati equations

$$A^T X E + E^T X A + C^T C - E^T X B B^T X E = 0$$

• • •



## Matrix equation solvers

Lyapunov equations

$$AXE^T + EXA^T + BB^T = 0,$$

$$AXA^T - EXE^T + BB^T = 0$$

Sylvester equations

$$AXE + FXB + C = 0$$

Bernoulli equations

$$A^T X E + E^T X A - E^T X B B^T X E = 0$$

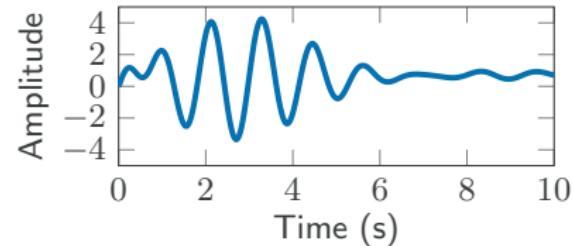
Riccati equations

$$A^T X E + E^T X A + C^T C - E^T X B B^T X E = 0$$

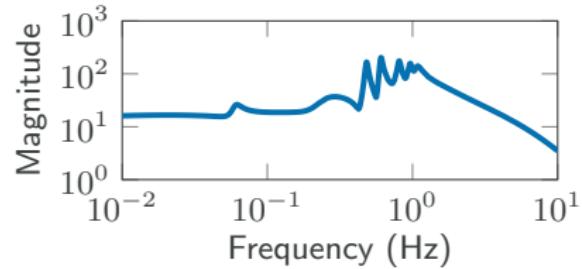
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## System evaluation

Time domain



Frequency domain



...

**SOLBT**



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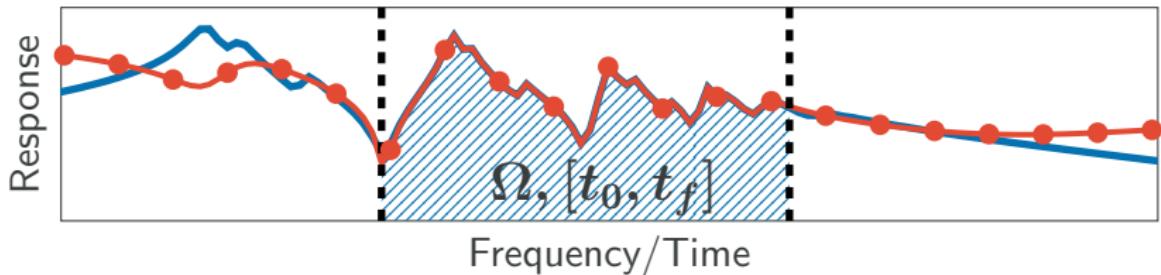
# SOLBT (Limited BT for Sparse Second-Order Systems)

- Author: S. W. R. Werner
- Academic supervisor: P. Benner
- Version: 3.0 (2021-04-27)
- License: BSD-2-Clause
- Started: 2019
- Dependencies: MATLAB ( $\geq$  2012b) with Control System Toolbox;  
Octave ( $\geq$  4.0.0) with Control Package
- Paper: P. Benner, and S. W. R. Werner:  
**Frequency- and time-limited balanced truncation for large-scale second-order systems**,  
Linear Algebra Appl., 623:68–103, 2021, doi:10.1016/j.laa.2020.06.024



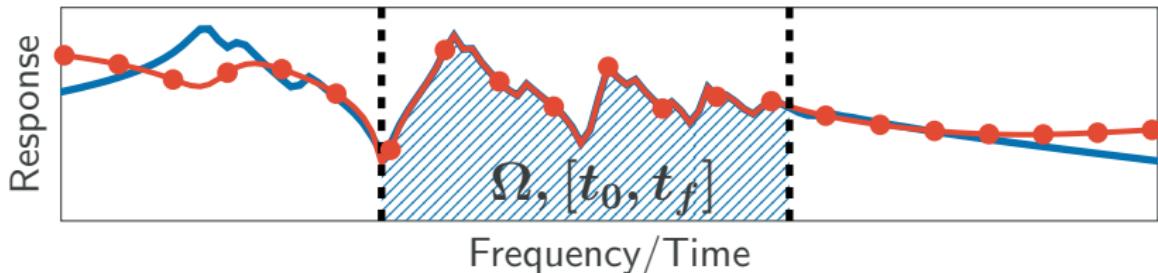
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## SOLBT: Features



- limited model reduction for large-scale sparse second-order systems

$$\begin{aligned} M\ddot{x}(t) + E\dot{x}(t) + Kx(t) &= B_u u(t), \\ y(t) &= C_p x(t) + C_v \dot{x}(t) \end{aligned}$$



- limited model reduction for large-scale sparse second-order systems

$$\begin{aligned} M\ddot{x}(t) + E\dot{x}(t) + Kx(t) &= B_u u(t), \\ y(t) &= C_p x(t) + C_v \dot{x}(t) \end{aligned}$$

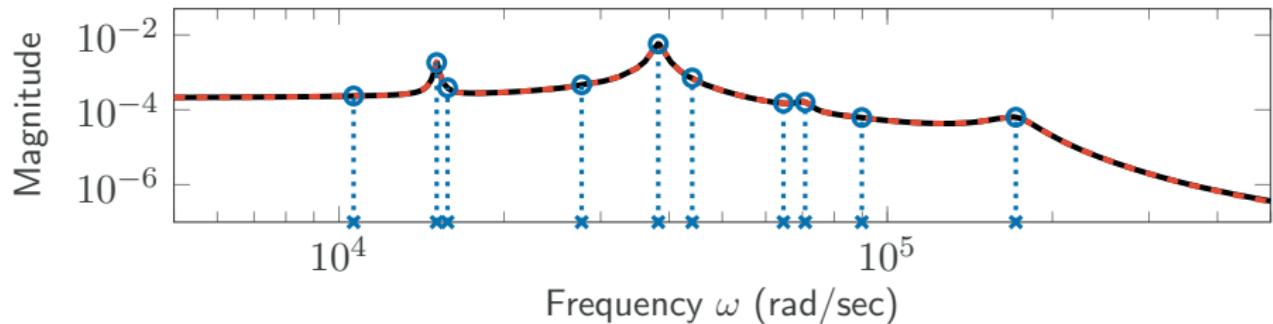
- projection-based solvers for limited Lyapunov equations

$$\begin{aligned} AX_\Omega E^\top + EX_\Omega A^\top + B_\Omega B_\Omega^\top + BB_\Omega^\top &= 0, \\ AX_\Theta E^\top + EX_\Theta A^\top + B_{t_f} B_{t_f}^\top - B_{t_0} B_{t_0}^\top &= 0, \end{aligned}$$

with  $B_\Omega = \operatorname{Re}\left(\frac{i}{\pi} \ln((A + i\omega_2 E)(A + i\omega_1 E)^{-1})\right)B$ , and  $B_{t_0,f} = e^{AE^{-1}t_{0,f}}B$

**SOMDDPA**

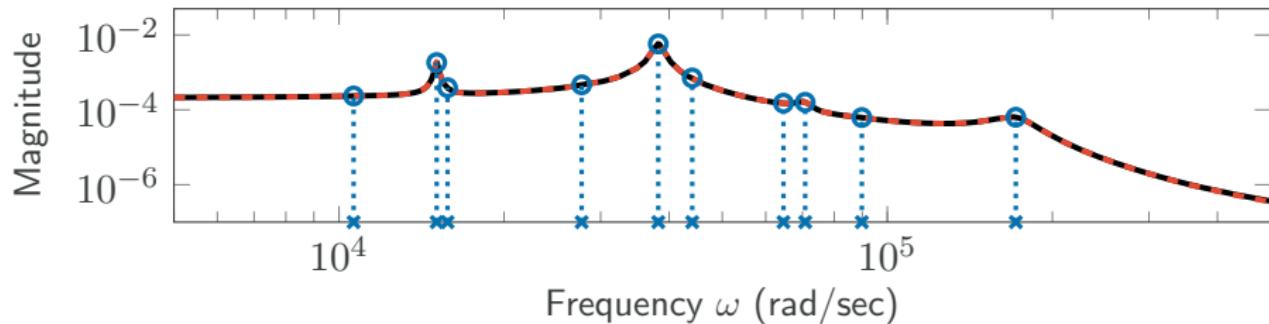
- Author: S. W. R. Werner
- Academic supervisor: P. Benner
- Version: 2.0 (2021-04-27)
- License: BSD-2-Clause
- Started: 2019
- Dependencies: MATLAB ( $\geq$  2012b); Octave ( $\geq$  4.0.0)
- Paper: J. Saak, D. Siebelts, and S. W. R. Werner:  
**A comparison of second-order model order reduction methods for an artificial fishtail**,  
at-Automatisierungstechnik, 67 (2019), pp. 648–667, doi:10.1515/auto-2019-0027



- dominant pole computation for modally-damped second-order systems

$$\begin{aligned} M\ddot{q}(t) + E\dot{q}(t) + Kq(t) &= B_u, \\ y(t) &= C_p q(t), \end{aligned}$$

with  $M, E, K > 0$  and  $EM^{-1}K = KM^{-1}E$



- dominant pole computation for modally-damped second-order systems

$$\begin{aligned} M\ddot{q}(t) + E\dot{q}(t) + Kq(t) &= B_u, \\ y(t) &= C_p q(t), \end{aligned}$$

with  $M, E, K > 0$  and  $EM^{-1}K = KM^{-1}E$

- eigenvalue computation based on Newton scheme and subspace acceleration

pyMOR



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pyMOR — Model Order Reduction with Python



## People

- maintainers: L. Balicki, R. Fritze, P. Mlinarić, S. Rave, F. Schindler
- # code contributors: 18



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## Info

- version: 2020.2.0 (2020-12-10)
- started: 2012
- license: BSD-2-Clause
- website: [pymor.org](https://pymor.org)



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## Info

- version: 2020.2.0 (2020-12-10)
- started: 2012
- license: BSD-2-Clause
- website: [pymor.org](https://pymor.org)

## Size

- # Python code lines: 19 615 (28 731 with tests, demos, ...)
- # documentation lines: 12 603 (17 739 with rst, tests, ...)



## Algorithms

MOR methods

## Data structures

vectors and matrices



Algorithms	Data structures
MOR methods	vectors and matrices

## Possible sources of high-dimensional data (backends)

- NumPy, SciPy
- PDE solver libraries (deal.II, DUNE, FEniCS, NGSolve, ... )
- proprietary software



## Algorithms

MOR methods

## Data structures

vectors and matrices

### Possible sources of high-dimensional data (backends)

- NumPy, SciPy
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- proprietary software

### Fundamental pyMOR classes

1. VectorSpace
2. VectorArray
3. Operator

## Three types of algorithms/implementations

1. abstract vectors, abstract operators (“good”)
2. concrete vectors, abstract operators (“bad”)
3. concrete vectors, concrete operators (“ugly”)

## Three types of algorithms/implementations

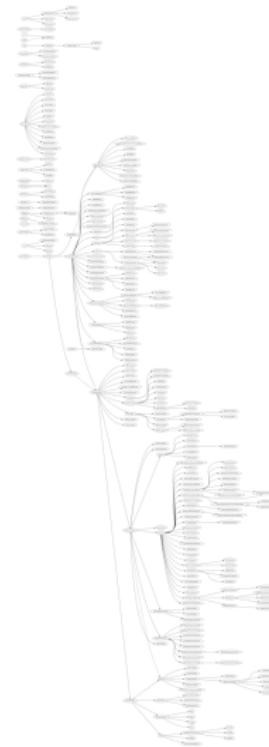
1. abstract vectors, abstract operators (“good”)
2. concrete vectors, abstract operators (“bad”)
3. concrete vectors, concrete operators (“ugly”)

## Example (linear system solvers)

- “ugly”: `scipy.linalg.solve`
- “bad”: `scipy.sparse.linalg.lgmres`
- “good”: `pymor.algorithms.genericsolvers.lgmres`



- `pymor.algorithms`
- `pymor.analyticalproblems`
- `pymor.bindings`
- `pymor.core`
- `pymor.discretizers`
- `pymor.models`
- `pymor.operators`
- `pymor.parallel`
- `pymor.parameters`
- `pymor.reductors`
- `pymor.tools`
- `pymor.vectorarrays`





## Algorithms and bindings

- (non)linear system solvers (SciPy, `lgmres`, `newton`)
- empirical interpolation (EIM, DEIM)
- eigenvalue solvers (`eigs`, SAMDP)
- Gram-Schmidt (bi)orthogonalization
- POD/SVD, HAPOD, randomized SVD
- matrix equation solvers (SciPy, Slycot, Py-M.E.S.S., LR-ADI, LR-RADI)
- time-stepping (explicit and implicit Euler)
- PDE solver library bindings (FEniCS, NGSolve)



## MOR methods

- reduced basis methods for parametric (in)stationary problems
- system-theoretic methods:
  - BT, LQGBT, BRBT, SOBT(p/v)
  - interpolation, IRKA, one-sided IRKA, TSIA, TF-IRKA, SOR-IRKA
  - MT (2021.1)
- neural network method for parametric problems

# Summary



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## Summary

<https://www.mpi-magdeburg.mpg.de/csc/software>

**PS:** More MOR software is in the MORWIKI:

[http://modelreduction.org/index.php/Comparison\\_of\\_Software](http://modelreduction.org/index.php/Comparison_of_Software)

[http://modelreduction.org/index.php/Further\\_Software](http://modelreduction.org/index.php/Further_Software)

**PPS:** How to write your own (MOR) Software:

J. Fehr, J. Heiland, C. Himpe, J. Saak: **Best Practices for Replicability, Reproducibility and Reusability of Computer-Based Experiments Exemplified by Model Reduction Software**; AIMS Mathematics 1(3): 261–281, 2016. doi:bsb2

J. Fehr, C. Himpe, S. Rave, J. Saak: **Sustainable Research Software Hand-Over**; Journal of Open Research Software 9(1): 5, 2021. doi:10.5334/jors.307