

# ESAPCA: Enabling the Analysis of Extremely Large Data Sets by Scalable and Hardware-Accelerated PCA and DMD



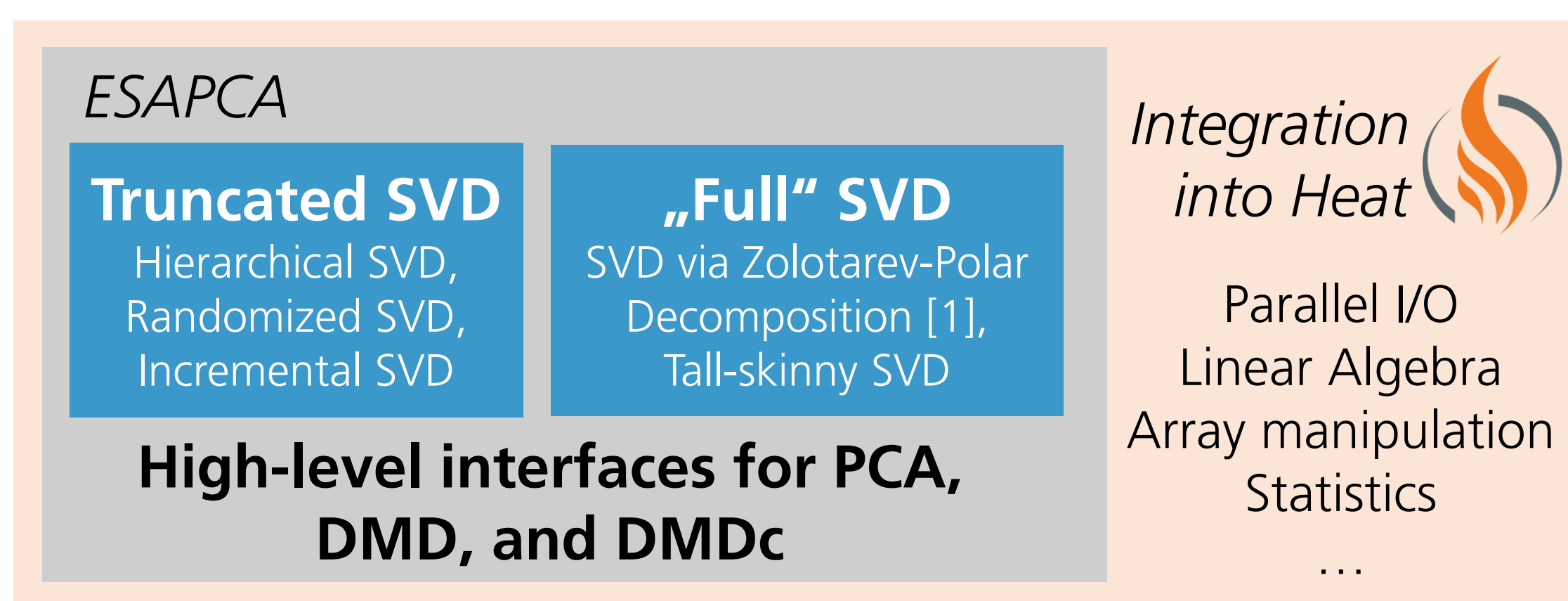
Fabian Hoppe, Philipp Knechtges, and Alexander Rüttgers

German Aerospace Center (DLR) – Institute of Software Technology – department High-Performance Computing – Cologne (Germany)

+ various colleagues from DLR, Research Center Jülich, and Karlsruhe Institute of Technology, and open-source contributors (for Heat-development in general)

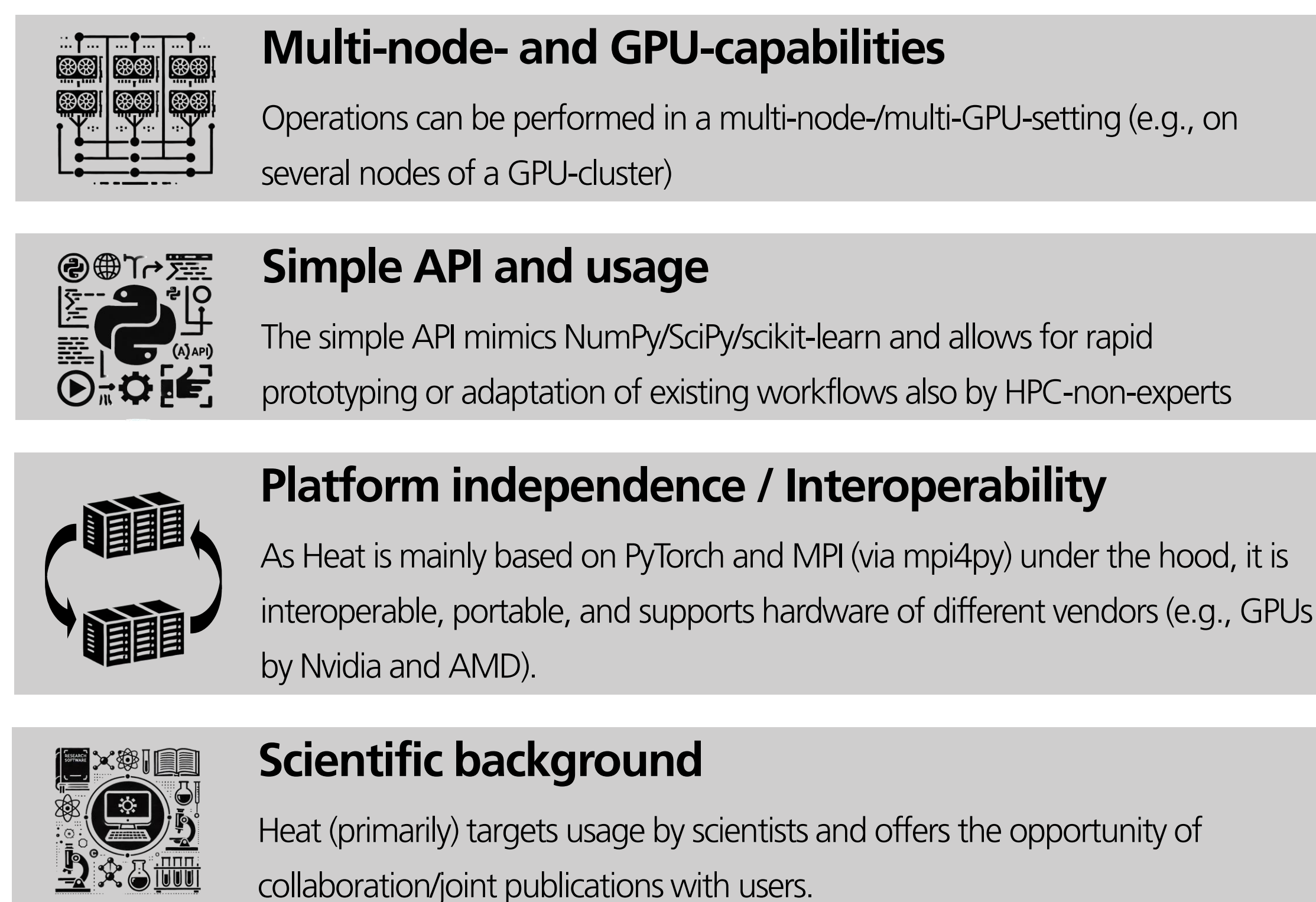
## The project ESAPCA

- Funded by the European Space Agency (ESA) as so-called Early Technology Development Project over 18 months (2024-2025)
- Goal:** develop a parallel, GPU-accelerated implementation of singular value decomposition (SVD) and related data science techniques, ...
  - ... capable of running on high-performance computing (HPC) systems, and ...
  - ... with a focus on easy usability and interoperability within the Python (NumPy/SciPy/scikit-learn) data science ecosystem
- Possible **applications** at ESA include, e.g.:
  - Data-driven modelling and prediction of thermospheric density
  - analysis of in situ measurements of powder bed solidification
- Implementation will build on the existing infrastructure for multi-node array computing within the open-source **Heat** research software library and will become part of this library



## Background: The library Heat [2]

- Open-source Python library for massively-parallel array computing and machine learning on CPU/GPU-clusters
- Vision:** *make array computing and machine learning/data analytics as simple on a supercomputer as it is on a workstation*
- Developed by DLR, Research Center Jülich, and Karlsruhe Institute of Technology (KIT) since 2018



- Basic data type: **DNDarray**, a distributed-memory- and GPU-capable counterpart of NumPy's **ndarray**
- Array creation, manipulation, and analysis routines, linear algebra operations, and classical machine learning algorithms, adapted to the parallel setting, of course.

Behind the scenes:

- SPMD programming model, hybrid-parallel and bulk-synchronous
  - automatic distribution of data across available processing resources by slab decomposition (split along one axis of the array)
  - eager execution
- ➔ Results in [2,3]: possible advantages w.r.t. RAM and time consumption compared to the task-based parallelization of Dask.

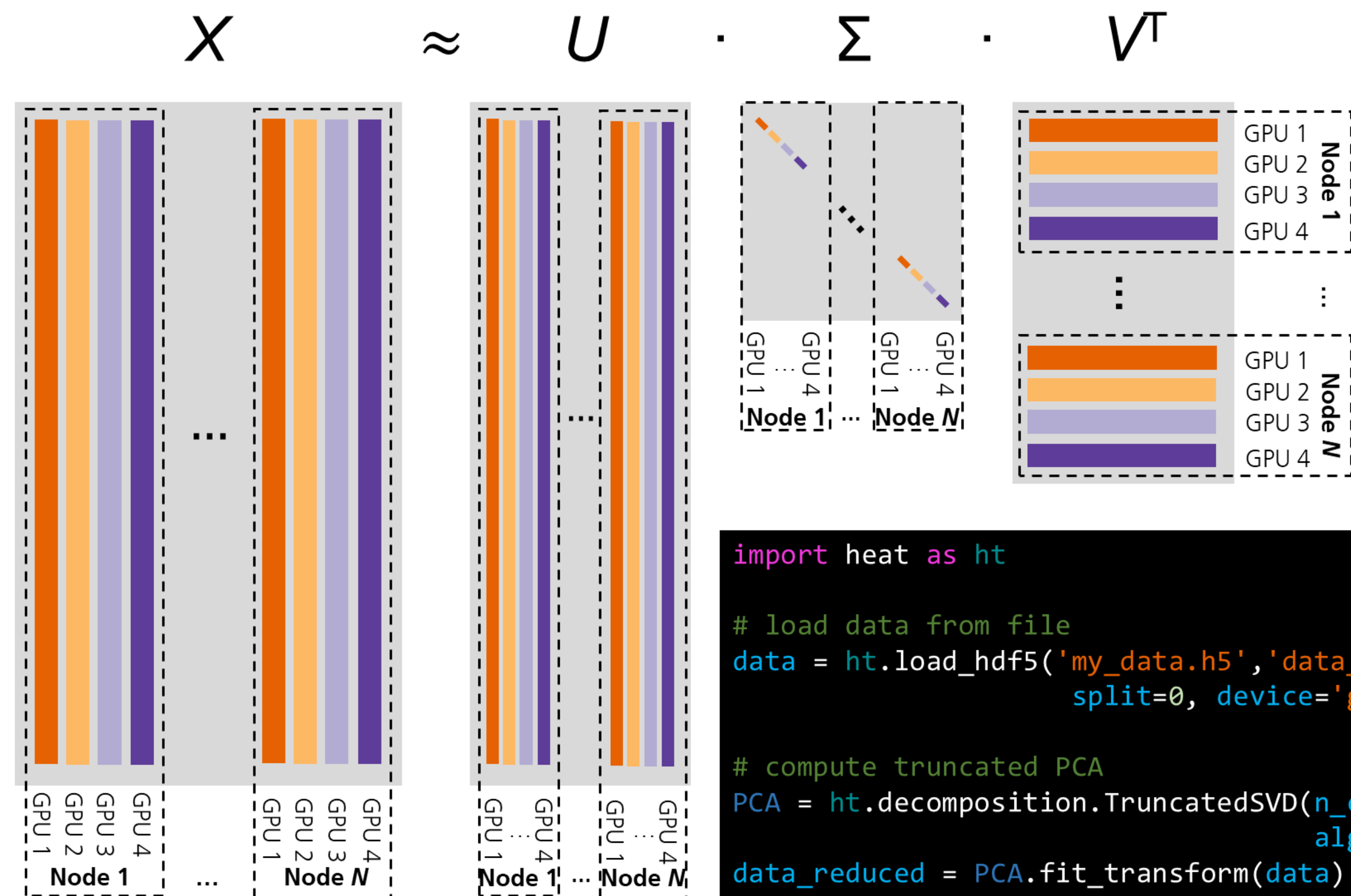


Illustration of the planned functionality: a simple scikit-learn-like API allows to compute the SVD of a huge matrix using several nodes of a GPU-cluster.

## Preliminary results

Preliminary experiments with tall-skinny matrices show promising results, e.g., for matrix-matrix multiplication (as, e.g., required for the computation of the Gramian matrix) and SVD both on Nvidia A100 and AMD MI250 GPUs:

**Weak scaling of runtime, memory, and energy consumption for matrix-matrix multiplication and SVD of tall-skinny matrices in Heat on up to 16 GPUs**

### Experiments

- matrix-matrix product  $A^T B$  of two tall-skinny matrices  $A$  and  $B$ , SVD of a tall-skinny matrix
- fraction of data<sup>¶</sup> = 1 corresponds to matrices of shape 1959552 x 40824 (matmul, 320GB per matrix) and 1239312 x 25819 (SVD, 128GB), respectively.
- "A100 (1)": weak scaling study with 40GB/8GB (matmul/SVD) of data per A100-GPU
- "A100 (2)"/"MI250": weak scaling study with 20GB/4GB (matmul/SVD) of data per A100- or MI250-GPU
- 1 MPI-process per GPU

### Hardware and Measurements

- 4 nodes of DLRs cluster terrabyte with 4 NVIDIA HGX A100 80GB 500W and 2 Intel Xeon Gold 6336Y 24C 185W 2.4GHz per node
- 2 nodes of KITs Future Technology Partition with 4 AMD MI250 and 2 AMD EPYC 7713 2.0GHz per node; since the MI250s are build as Multi Chip Modules (MCM) each MI250 is handled as two GPUs with 64GB RAM each
- Measurements using the hardware counters and the Python package `perun` [4]

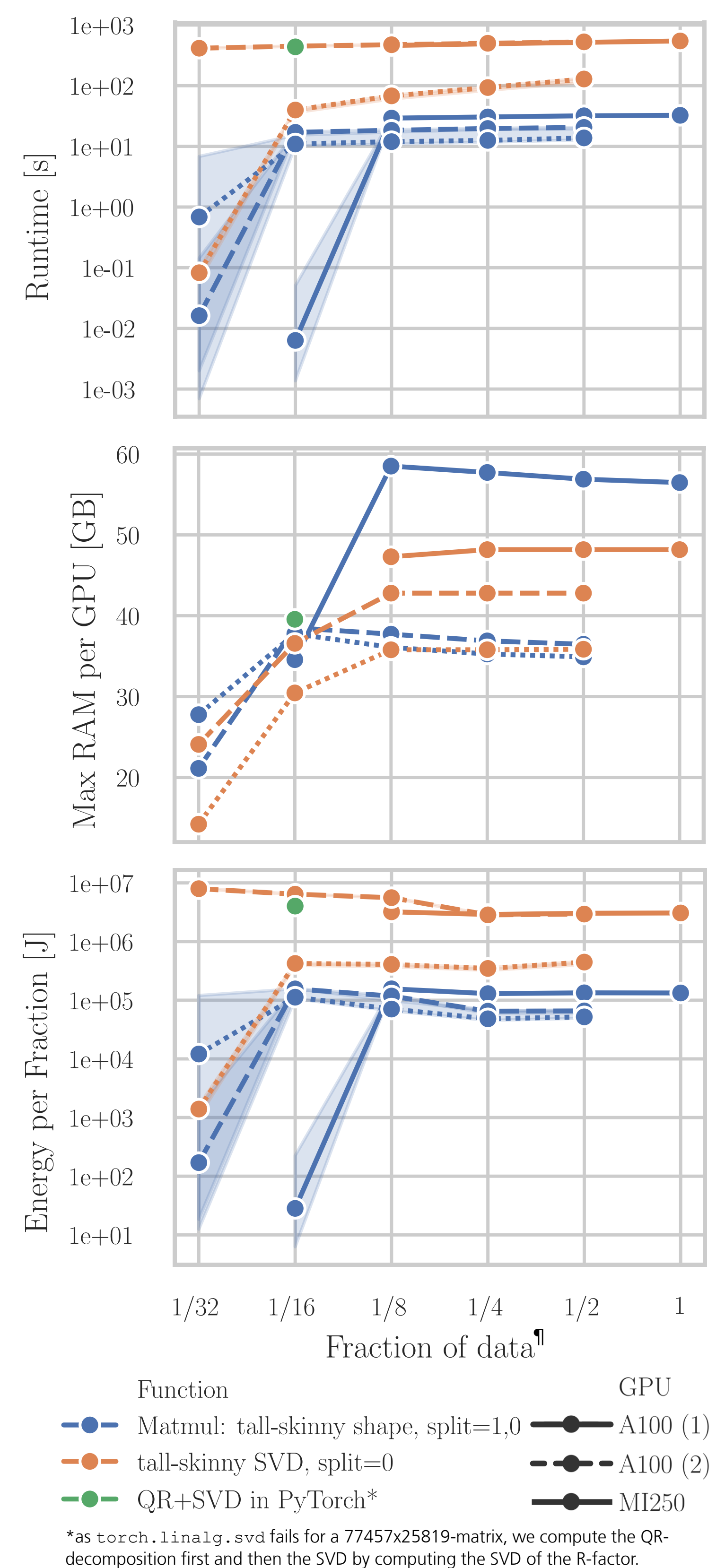
### Software

- OpenMPI 4.1, PyTorch 2.5.1 with ROCm 6.2.2 (MI250) or CUDA 11.8 (A100), Heat 1.6-dev

<sup>¶</sup>The reason for scaling by "fraction of data" instead of by number of nodes or number of GPUs is due to the fact that we compare systems with a different number of GPUs per node and GPUs with a different amount of RAM per GPU.

## References

- Y. Nakatsukasa, R. W. Freund. *Computing fundamental matrix decompositions accurately via the matrix sign function in two iterations: The power of Zolotarev's functions*. SIAM Review 58, 3, 2016.
- M. Götz et al. *Heat – a Distributed and GPU-accelerated Tensor Framework for Data Analytics*. In: 2020 IEEE International Conference on Big Data, 2020.
- F. Hoppe, J.P. Gutiérrez Hermosillo Muriedas, M. Tarnawa, P. Knechtges, B. Hagemeyer, K. Krajsek, A. Rüttgers, M. Götz, and C. Comito. *Engineering a large-scale data analytics and array computing library for research: Heat*. Accepted at ECEASST, 2024.
- J. P. Gutiérrez Hermosillo Muriedas et al. *perun: Benchmarking Energy Consumption of High-Performance Computing Applications*. In: Euro-Par 2023: Parallel Processing, 2023.



This research is supported by the European Space Agency through the Open Space Innovation Platform (<https://ideas.esa.int>) as a Early Technology Development Agreement and carried out under the Discovery Program ESA Early Technology Development (Research Agreement No. 4000144045/24/NL/GLC/ov). Disclaimer: The view expressed in this publication can in no way be taken to reflect the official opinion of the European Space Agency.



<https://activities.esa.int/4000144045>

This work was performed on the NHR@KIT Future Technologies Partition testbed funded by the Ministry of Science, Research and the Arts Baden-Württemberg and by the Federal Ministry of Education and Research. Moreover, the authors gratefully acknowledge the computational and data resources provided through the joint high-performance data analytics (HPDA) project "terrabyte" of the German Aerospace Center (DLR) and the Leibniz Supercomputing Center (LRZ).

